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DIRECTIONS IN DEVELOPMENT  
**Poverty**

# The Poverty and Welfare Impacts of Climate Change

*Quantifying the Effects, Identifying  
the Adaptation Strategies*

Emmanuel Skoufias, Editor



THE WORLD BANK



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**THE WORLD BANK**  
Washington, D.C.

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1818 H Street NW  
Washington DC 20433  
Telephone: 202-473-1000  
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ISBN (paper): 978-0-8213-9611-7  
ISBN (electronic): 978-0-8213-9612-4  
DOI: 10.1596/978-0-8213-9611-7

Cover photo: Panos  
Cover design: Naylor Design

*Library of Congress Cataloging-in-Publication Data has been Applied for.*

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# Acknowledgments

We wish to thank Syud Amer Ahmed for reviewing and commenting on all of the chapters and Milan Brahmbhatt, Michael Toman, Jaime Saavedra, and colleagues from the World Bank's Poverty Reduction and Equity team for providing useful comments on earlier versions of chapter 2. Abla Safir also provided useful comments on the background papers for chapters 4 and 5, while Hector V. Conroy assisted with the interpolation of the weather data for Mexico used in chapters 4 and 5. Finally, we are deeply grateful to Mary Anderson for her excellent editorial assistance.



## Abbreviations

ATT	average treatment effect on the treated
BAU	business as usual (impact of climate change without emission abatement)
ENN	National Nutrition Survey (Encuesta Nacional de Nutrición)
GDD	growing degree days
GDP	gross domestic product
GHG	greenhouse gas
GTAP	Global Trade Analysis Project
IAM	integrated assessment model
IDT	Program for Underdeveloped Villages (Inpres Desa Tertinggal)
IFLS	Indonesian Family Life Survey
IMTA	Mexican Water Technology Institute (Instituto Mexicano de Tecnología del Agua)
IPCC	Intergovernmental Panel on Climate Change
MxFLS	Mexican Family Life Survey
PAGE	Policy Analysis of the Greenhouse Effect (integrated assessment model)
PCE	private consumption expenditure

PDM-TKE	Regional Empowerment to Overcome the Impact of Economic Crisis
PPP	purchasing power parity
PROGRESA	Education, Health, and Nutrition Program (Programa de Educación, Salud y Alimentación)
PSM	propensity score matching
RICE	Regional Integrated Model of Climate and the Economy
SATT	sample average treatment effect for the subpopulation of the treated
SD	standard deviation
SRES	Special Report on Emissions Scenarios (of the IPCC)
WMO	World Meteorological Organization

*All dollar amounts are U.S. dollars unless otherwise indicated.*

## CHAPTER 1

# Disquiet on the Weather Front: Implications of Climate Change for Poverty Reduction

Emmanuel Skoufias

### Introduction

The continued decline in global poverty over the past 100 years—particularly in the past three decades—is a remarkable achievement. In 1981, 52 percent of the world population lived on less than \$1.25 a day.<sup>1</sup> By 2005, that rate had been cut in half, to 25.0 percent (Chen and Ravallion 2010), and by 2008 to 22.2 percent (World Bank 2012). Preliminary estimates for 2010 indicate that the extreme poverty rate has fallen further still; if follow-up studies confirm this, the Millennium Development Goal (MDG) of halving world poverty will have been reached five years early (World Bank 2010).<sup>2</sup>

In recent years, poverty reduction has continued in most countries, even after the financial, food, and fuel shocks of 2008–09. Although poverty remains widespread in South Asia and Sub-Saharan Africa, progress has been substantial: Extreme poverty fell in South Asia from 54 percent in 1990 to 36 percent in 2008 (World Bank 2012). In Sub-Saharan Africa, where population growth exceeded the rate of poverty reduction, the number of extremely poor people increased from 290 million in 1990 to 356 million in 2008, yet over 2005–08, the

region's poverty rate nonetheless "fell 4.8 percentage points to less than 50 percent—the largest drop in Sub-Saharan Africa since international poverty rates have been computed," according to the latest edition of the *World Development Indicators (WDI)* (World Bank 2012). Although progress has been slower at the \$2-a-day poverty line, the *WDI* noted that an increase in the absolute number of people living on \$1.25–\$2.00 a day reflects both the upward movement from extreme poverty and "the vulnerabilities still faced by a great many people in the world."

The positive overall trend is expected to continue, especially if developing countries manage to sustain the rapid per capita income growth rates they achieved over the past decade. On that score, too, there is cause for optimism. The April 2012 edition of the International Monetary Fund's (IMF) *World Economic Outlook* predicted (despite continuing uncertainty over Europe's prospects) a post-financial-crisis acceleration of economic growth overall by 3.5 percent in 2012 and by more than 4.0 percent by 2013 (IMF 2012).

Indeed, the emerging markets of Asia, Latin America, and Eastern Europe should regain some collective momentum, with overall growth of 5.7 percent in 2012 and 6.0 percent in 2013—and India and China gaining by 7.0 percent and 8.0 percent, respectively (IMF 2012). If developing countries maintain their income growth rates, poverty headcounts at the \$1- or \$2-per-day income levels could turn out to be almost obsolete as measures of well-being over the next 50 to 100 years.

Amid this good news, however, strange new weather patterns have been unfolding worldwide. Concerns have grown that climate change could corrode or even reverse progress on poverty reduction. Scientific evidence shows that the Earth's mean surface temperature is already rapidly raising because of increased greenhouse gas (GHG) emissions (IPCC 2007). The resultant pressure of climate change on environmental systems could particularly imperil the livelihoods of rural poor people—a population that will continue to grow despite increasing urbanization.

While the eyes of the world have been riveted on polar bears, Antarctic penguins, and other endangered inhabitants of the Earth's shrinking ice caps, relatively few researchers have turned serious attention—until recent years—to quantifying the prospective long-term effects of climate change on human welfare.

Even before rising sea levels may send coastal residents packing for higher ground, rural populations are arguably among the first to feel the effects of increasingly erratic weather patterns as well as the most vulnerable to those effects. To examine even the short-term impact of climate

change on those populations—and the effectiveness (or not) of their adaptation strategies—is to provide a preview of a global problem.

### **Climate Change in a Rural Context**

Climate change is likely to reduce agricultural productivity, especially in the tropical regions, and to directly affect poor people's livelihood assets—including health, access to water and other natural resources, homes, and infrastructure (World Bank 2010). Moreover, increasing climatic variability—manifesting as more frequent and erratic weather extremes, or “weather shocks”—will likely make poor households even more vulnerable, which could in turn exacerbate the incidence, severity, and persistence of poverty in developing countries.

Such concerns are rooted in these countries' greater dependence on agriculture and other climate-sensitive natural resources for income and well-being, compounded by their lack of sufficient financial and technical capacities to manage increasing climate-related risks. In this context, climate change represents a serious challenge to poverty reduction efforts around the globe.

This volume not only surveys the research terrain concerning the effects of climate change on poverty but also looks closely at vulnerable rural populations (in a developing country, Indonesia, and in the newly industrialized Mexico) where weather shocks have measurable short-term if not immediate effects on the farming livelihoods many depend on for both income and subsistence. The low-income farmers of rice in Indonesia and of corn and other staple crops in Mexico are at the human forefront of climate change.

Climate change is a long-term problem that has been unfolding over many decades.<sup>3</sup> Despite uncertainty over the exact magnitudes of the global changes in temperature and precipitation, climatologists and policy makers alike widely accept that climate variability will likely deviate significantly from its historical patterns (IPCC 2007). It is likely to lead not only to changes in the mean levels of temperatures and rainfall but also to a significant increase in the variability of climate and in the frequency of extreme weather events.

Erratic weather and increased climatic variability (weather shocks) will affect agricultural productivity, which could translate into reduced income and reduced food availability at the household level. Consequently, much depends on the effectiveness of households' risk management strategies. Considering that millions of poor households in rural areas all over

the world depend on agriculture, there are increasing concerns that the change in climatic variability patterns will seriously challenge development efforts globally. In view of this imminent threat to the poor, it is critical to deeply understand the effectiveness of household adaptation strategies as well as targeted measures that could mitigate the poverty impacts of erratic weather.

### **Pioneering Research Models**

Climate change may affect household welfare through a variety of channels, and the emerging literature has focused largely on the impacts on agricultural productivity, given its close nexus with weather conditions.

The earliest estimates of the impact of climate change on poverty, to our knowledge, are based on an integrated assessment model (IAM)—a general equilibrium model using microevidence to quantify the socioeconomic dimensions of climate change and aggregate those measurements to estimate net effects on national incomes.<sup>4</sup> IAMs (which chapter 2 discusses in more detail) model climate-economy interactions and, in the policy sphere, form the basis of many recommendations for GHG emission control.

Ahmed, Diffenbaugh, and Hertel (2009) is the only study to date to apply a general equilibrium model to estimate the channels and poverty impacts of extreme weather events such as extreme heat, droughts, and floods. They apply the model to 16 countries, comparing two 30-year periods a century apart (1971–2000 and 2071–2100) in the simulations under the Intergovernmental Panel on Climate Change's (IPCC) A2 climate-change scenario (under which global mean temperature increases by 3.9°C by 2100).<sup>5</sup> In the simulations, all 16 countries exhibit substantial increases in the occurrence and magnitude of extreme heat events, with the occurrence of the present 30-year-maximum event increasing by more than 2,700 percent in parts of the northern Mediterranean and the magnitude of the 30-year-maximum event increasing by 1,000–2,250 percent (or even more) in much of central Africa. Most of the countries also display increases in the occurrence and magnitude of extreme dry events, with peak changes of greater than 800 percent and 60 percent, respectively, occurring over Mediterranean Europe.

The magnitude and spatial heterogeneity of changes in climate volatility suggest that the impacts on poverty could be large and heterogeneous as well. Among the 16 countries analyzed, those with the highest shares of populations entering poverty because of these extreme events include

Bangladesh, Malawi, Mexico, Mozambique, Tanzania, and Zambia. For example, in Malawi and Zambia, a simulated 75 percent decline in grains productivity causes the poverty headcount to increase by about 7 percentage points relative to the countries' total populations.

### **Introducing Heterogeneity**

Although recent research generally agrees on the significant overall negative impact of global warming on agricultural productivity and household welfare, the studies also find considerable heterogeneity in these impacts—even within a single country. As chapter 2 explains further, a relatively recent study of Brazil found that, on average, agricultural output per hectare could decrease by 18 percent by 2040 as a result of climate change but that, at the municipality level, the impacts could range from a decrease of 40 percent to an increase of 15 percent (Assunção and Chein Feres 2009). Although the authors predict that the poverty rate of rural areas in Brazil will increase by 3.2 percentage points overall, again, there is significant geographical variation, with already-poor regions being more affected than more prosperous regions. Although the Brazilian study highlights the importance of capturing heterogeneous results, its major shortcoming is its overestimation of the impacts of climate change on poverty because it does not take into account the potential increase in mean per capita income from economic growth over the next 40 years.

In another recent study, in India, household-level data also showed significant heterogeneity in the impact of climate on per capita consumption across the country's rural districts (Jacoby, Rabassa, and Skoufias 2011). The authors estimated that increases in mean surface temperature by 2040 could lead to consumption impacts ranging from no change in some locations to an 11 percent decrease in others.

### ***Importance of Diversified Household-Level Data***

Such widely ranging outcomes are linked in the literature to several inter-related variables, including geographical location and household-specific characteristics such as the following:

- Whether the household is a net producer or a net consumer of food
- The household's current and potential (diversified) income sources
- The types of assets owned by the household
- The household's ability to adapt to income disruptions and smooth consumption

- The structure of household expenditures
- The household's ability to access credit or social safety-net programs.

For instance, climate change (or even one growing season's weather shock) might reduce physical productivity on a farming household's cereal land. But a general decline in agricultural productivity will also raise food prices, benefiting that same household as long as it is a net producer of cereals. Also, the extent to which a decline in agricultural productivity translates into lower rural wages depends on the diversification of the local economy and the ability of labor to move into other occupations.

Further, climate change impacts tend to be regressive, falling more heavily on the poor than the rich. This result can be decomposed into three effects, as chapter 2 discusses further:

- *Returns to land*—the rich lose proportionately more than the poor because they hold the lion's share of land.
- *Returns to labor*—productivity declines translate into wage reductions, which is distributionally neutral.
- *Cereal prices*—rising prices affect the poor more than the rich.

Some broader perspectives, also discussed in chapter 2, look at economywide impacts using a general equilibrium model of global production, trade, and income distribution.

A key finding in these studies is that the most significant climate change impacts on poverty are likely to occur among urban wage laborers, who are the most negatively affected by food price increases. With food being a major expenditure, urban residents' consumption falls as prices rise, pushing many below the poverty threshold of consumption. In contrast, agricultural, self-employed households in rural areas are less affected because they benefit from higher prices: as consumers, they are generally hurt by the adverse productivity shock, but as producers, they also tend to benefit from the higher food prices.

### ***Role of Adaptation and Risk Management Strategies***

The effect of climate change on poverty also depends on the extent of households' adaptation to emerging circumstances. Jacoby, Rabassa, and Skoufias (2011) calculate the welfare benefits from autonomous adaptation in agriculture in India. In this context, "autonomous adaptation" can be defined as market-based responses to climate change by

individuals, households, or firms, typically by adjustments over time in their production and consumption patterns.<sup>6</sup>

These forms of adaptation (that is, changes in cropping patterns, input use, and technology) reduce the average long-term loss in per capita consumption from climate change by about half (the decline in consumption is 11 percent in the case of a weather shock, compared with 6 percent when autonomous adaptation is factored in) (Jacoby, Rabassa, and Skoufias 2011).

Migration, the most extreme adaptation measure, can also help reduce the potential longer-term welfare impacts of climate change. In Brazil, allowing for labor mobility across sectors or across municipalities reduces the climate-based increase in the rural poverty rate from 3.2 percentage points to 2.0 percentage points (Assunção and Chein Feres 2009).

These studies of adaptation show that households' adaptability to climate change over the longer term is vital and that this ability can be strengthened by disseminating information about longer-term risks and anticipatory investments. However, longer-term impact reduction through adaptation would not necessarily diminish the substantial adjustment costs. The impact on household welfare will depend in part on the risk management strategies employed by households,<sup>7</sup> how effective those strategies are in mitigating the impacts, and the general distribution of impacts across many different households. Some mitigating factors include the following:

- Autonomous adaptation, such as the ability to migrate or switch employment between agricultural and nonagricultural occupations
- Policy-induced adaptation through prices and explicit government safety-net programs, such as access to credit and insurance (Cline 2007; Hertel and Rosch 2010)
- Distribution of productive endowments (such as irrigated and nonirrigated land or skilled and unskilled labor)
- Rural households' dual role as both consumers and producers of food—and whether they are net consumers or net producers.

On a global scale, however, researchers should bear in mind that economic growth—often absent in discussions of the future impacts of a warming world—will have a tremendous ameliorating effect as food expenditures decrease as a share of total expenditures and as the agriculture sector decreases relative to national gross domestic product (GDP) (Nordhaus 1993).

## Contributions of This Volume

Profound uncertainties pervade every stage of climate-change modeling, starting with the foundation—climatic reaction to rising GHG concentrations—and proceeding to the economic and social dimensions. Yet to be discerned are the extent of future output growth, the pace and direction of technological change (particularly for low-carbon energy sources), the shift in migration patterns, and the economic and ecological responses to changing climate and how impacts should be discounted.

Given these uncertainties and limitations in knowledge surrounding climate change, its impact on economic growth, and the impacts of growth on poverty, the analyses in this volume should be viewed as indicative only of the *potential* consequences of climate change on global poverty. Yet these chapters do advance the consideration of key research issues and their implications for poverty reduction and widespread adaptation during the world's transition to a new climate equilibrium. Their distinct contributions, as further described in the synopses below, include the following:

- Emphasis on providing quantitative evidence on the impacts of climate change on different dimensions of household welfare: consumption and child health (the latter measured by a standard nutritional indicator—child height)
- Use of historic weather data, matched as closely as possible to the households' location, to analyze the relationship between weather and welfare
- Attention to timing of climatic shocks, their potential channels of impact, household heterogeneity in coping with and adapting to such shocks, and the role of public programs in mitigating the effects of the shocks.

### ***Chapter 2—The Forecast for Poverty: A Review of the Evidence***

Numerous studies have examined the impacts of natural disasters and extreme weather-related shocks on the economic and social dimensions of welfare. In a literature review, Emmanuel Skoufias, Mariano Rabassa, and Sergio Olivieri highlight three main strands of analysis:

- Economywide growth models that incorporate climate-change impacts to work out consistent scenarios for how climate change might affect the path of poverty

- Sector-specific studies, primarily those focusing on the poverty impacts of climate change in the agricultural sector
- Studies that explore how past climate variability has affected poverty.

As their review shows, most estimates of the poverty impacts tend to ignore the effect of aggregate economic growth on poverty and household welfare. The empirical evidence available to date suggests that climate change will slow the pace of global poverty reduction, but the expected poverty impact will be relatively modest—far from reversing the major decline in poverty expected over the next 40 years as a result of continued economic growth.

In addition, the authors find that the sector-specific studies—focusing on how climate change may affect agricultural yields, for example—are generally poor predictors of the poverty impacts of climate change at the national level because of heterogeneity in households' ability to adapt. Unsurprisingly, the impacts of climate change are generally regressive—falling more heavily on the poor than on the rich—but the most vulnerable population of all may be the urban wage-labor-dependent stratum because, as net food consumers rather than net food producers, they may have greater exposure to food price increases. Agricultural households are less exposed because, although weather shocks may hurt productivity and reduce their incomes, such households also would benefit to some extent from the higher food prices.

Certain key messages and policy considerations can be extracted from the surveyed studies, which are quite heterogeneous in terms of data, methods, and focus. Some of these messages are caveats: For example, although many previous studies have been unduly pessimistic for failing to incorporate sufficient economic growth assumptions, continued growth and poverty reduction in developing countries will depend on whether those countries can maintain growth while also burning less fossil fuel. In addition, although aggregate projected damages from climate change are projected to be low to moderate through the middle of the 21st century, a longer timeline could see larger effects on poverty, especially if more extreme climate-change scenarios play out. Nor do the aggregate figures reflect the likelihood that Africa and South Asia could see more substantial climate-induced increases in poverty.

The good news is that the same policies that reduce the poverty impact of climate change also promote sound development, poverty reduction, and economic growth in general. The remaining chapters discuss some of these policies in a country-specific rural context.

### ***Chapter 3—Too Little, Too Late: Welfare Impacts of Rainfall Shocks in Rural Indonesia***

Emmanuel Skoufias, Roy S. Katayama, and Boniface Essama-Nssah use data from rural Indonesia to consider the effects of two rainfall-related shocks: (a) a delay in monsoon onset and (b) a significant shortfall of rain during the 90-day post-onset period. Focusing on households with family farm businesses, they find that rice-farming households in areas experiencing low rainfall following the monsoon's onset are negatively affected: the shortfall is associated with a 14 percent reduction in those households' per capita expenditures. Moreover, in the face of weather shocks, these households protected their food expenditures at the expense of nonfood expenditures. The findings are consistent with households' reduction of expenditures on health and education—reductions that ultimately may have a longer-term effect on poverty by reducing investment on the human capital of children.

The Indonesia study also sheds light on potential policy instruments that might moderate the welfare impact of climate change. Access to credit and public works projects in communities can help households cope with weather shocks and thereby play a strong role in protection. This is an important consideration for the design and implementation of adaptation strategies.

### ***Chapter 4—Timing Is Everything: How Weather Shocks Affect Household Welfare in Rural Mexico***

Skoufias and Katja Vinha examine whether climatic variability—namely, deviations of rainfall and temperature from their long-run means—significantly affects the average well-being of rural households in Mexico. They report that the timing of the rainfall or temperature shock (in relation to the annual growing cycle) makes a substantial difference in the shock's estimated impact on welfare.

For example, during the period studied, per capita expenditures were 14 percent higher if the preceding agricultural year (October to September) was at least one standard deviation drier than the average of a previous 35-year period (1951–85). However, if a rainfall shock (either a drier-than-average or a wetter-than-average period) were to occur during the wet season of that year (April to September), the shock did not appear to significantly affect per capita expenditures.

Furthermore, the results show that a household's ability to protect its consumption from weather shocks depends not only on the nature of the shock and when in the agricultural year the shock occurs but also on

a household's particular climatic region. Some households cannot smooth consumption; in particular, those in arid climates were prone to lower expenditures after either colder- or drier-than-average weather at certain points in the agricultural year. Differences in household vulnerability (ability to smooth consumption) also depend on other location characteristics, including households' proximity and access to transportation (bus stations).

Because of the great degree of heterogeneity in household responses to different weather shocks, the results highlight the necessity to account for the underlying climatic variation through more region-specific analyses, more fine-tuning of shock definitions, and inclusion of more municipalities. Only then can the effectiveness of both autonomous (household-level) and government risk management strategies (such as social safety-net programs)—and the potential implications of each for public policy—be better evaluated.

### ***Chapter 5—Growing Precious Resources: Climate Variability and Child Height in Rural Mexico***

The final chapter in this volume turns to a health indicator, child height, as another way to measure the impact of weather shocks on poverty. The shocks—defined as either rainfall or growing degree days (GDD, a cumulative measure of temperature) that deviate by more than one standard deviation from their respective long-run means—are assessed in terms of their impact on the growth of rural children in Mexico between 12 and 47 months of age.

Exploring the consequences of weather on the health of these vulnerable individuals, Skoufias and Vinha found three consistent results:

- After a positive rainfall shock (significantly increased rainfall), children were shorter than they would have been under normal conditions, no matter where they lived or the altitude.
- Negative temperature shocks (significantly cooler temperatures) also had a negative impact on height, albeit only in certain regions: the central and southern parts of the country as well as higher altitudes.
- Positive temperature shocks (unusually warm weather) had no average impact on the overall child population being measured. However, certain subpopulations (boys, children between 12 and 23 months at the time of measurement, and children of less-educated mothers) were negatively affected.

The results suggest that either reduced consumption, increased communicable disease prevalence, or both potentially contribute to negative effects on child growth. Again, further research is warranted considering the evidence linking childhood health to various aspects of later well-being, including educational outcomes and adult cognitive abilities, productivity, and employment.

## **Conclusions and Some Policy Implications**

Climate change may slow the pace of global poverty reduction but will probably not reverse the progress already made, assuming (unlike most estimates to date of the poverty impacts of climate change) that aggregate economic growth will continue to reduce poverty and improve household welfare. However, some qualifications are in order:

- Much of the poverty impact is likely to be concentrated in Africa and South Asia, both of which would see more substantial increases in poverty relative to a baseline without climate change.
- The occurrence of less probable but more extreme climate damage scenarios would naturally result in larger poverty increases.
- Aggregate projected damages are relatively low over the time horizon analyzed here (to mid-21st century). As climate change continues to unfold during this and the next century, aggregate damages could be substantial and have a larger effect on poverty.

### ***Adaptation Is Key***

Recent empirical studies confirm that changes in climatic means and variability can have substantial impacts on agricultural output, household welfare, and poverty, but that there is considerable heterogeneity in outcomes based on geographical location; a household's assets and income-earning potential; whether the household is a net agricultural producer or consumer; and the opportunities for adaptation and risk management available to the household. Effective adaptation strategies can reduce the poverty impacts of climate change substantially.

### ***Policy Makers' Role***

Policy makers can do much to help the poor better adapt to and cope with climate change and extreme weather events without compromising human capital, which is the long-term foundation of household welfare. Fortunately, many of the policies that can effectively mitigate, or help

people adapt to, the impacts of climate change on poverty are the same strategies that promote sound development, poverty reduction, and economic growth in general:

- Creating well-targeted, scalable safety nets
- Improving the access of poor people to credit and insurance markets
- Investing in human capital to increase employment opportunities for the poor
- Reducing impediments to occupational mobility and facilitating migration to help poor people reach areas with better economic opportunities
- Improving governance of common-pool natural resources
- Enhancing international trade to smooth the food-price and other commodity-related impacts of regional or country-specific climate shocks
- Investing in transportation and communication infrastructure
- Investing in irrigation and water management to anticipate and address extreme precipitation events
- Investing in adaptive agricultural research and in information and extension services.

The regressive impacts of climate change mentioned previously, combined with the emerging evidence that access to social protection and credit programs moderate the welfare impacts of climate change, suggest that the establishment of safety-net programs and the strengthening of the institutions to implement and scale up such programs should be a critical component of country-level adaptation strategies.

In particular, countercyclical safety-net systems such as conditional and unconditional cash transfers; workfare programs (food- or cash-for-work); and social funds (community-level programs in infrastructure, social services, training, and so on) can have immediate payoffs because they enable countries to deal with economic crises and other shocks that may not be related to climate change and climatic variability.

The need for climate action and leadership has entered a watershed period. At the December 2011 United Nations Conference on Climate Change in Durban, South Africa, the world's governments struggled anew to reach a comprehensive, binding global agreement to limit ever-rising GHG emissions lest the IPCC's projected climate-change scenario of catastrophic, irrevocable climate change become a reality. The Durban Platform for Enhanced Action, adopted by all 194 participating countries, at least set a direction for continuing climate negotiations; and a Green

Climate Fund was also launched to help developing countries in their climate-change adaptation and mitigation efforts.

Meanwhile, rural households will keep using time-tested, traditional methods to adapt as best they can to a world of increasingly unpredictable weather shocks. It is incumbent on local, regional, country-level, and multilateral leaders to help the most vulnerable to prepare for, and respond to, these unknown perils ahead. There is no better time to bring innovative leadership and political will to bear in a way that aligns climate-change preparation with development objectives and continuing poverty-reduction strategies.

## Notes

1. The World Bank defines extreme poverty as per capita income of less than \$1.25 per day in 2005 purchasing power parity (PPP) terms; it represents the mean of the poverty lines found in the poorest 15 percent of countries ranked by per capita consumption. The median poverty line for developing countries is \$2 a day in 2005 PPP terms. Poverty measures are prepared by the World Bank's Development Research Group. For more information on poverty definition, measurement, and trends, see <http://www.worldbank.org/poverty/> and <http://poverty.net.org/>. For details on data sources and methods used in deriving the World Bank's latest estimates, see <http://iresearch.worldbank.org/povcalnet>.
2. For more information about the United Nations MDGs, see <http://www.un.org/millenniumgoals>.
3. According to the Intergovernmental Panel on Climate Change, "climate" refers to the statistical description of quantities such as temperature and precipitation (in terms of mean and variability, for example) over a period of time ranging from months to thousands of years. The norm is 30 years, as defined by the World Meteorological Organization. "Climate" therefore differs from "weather"—the atmospheric conditions in a given place at a specific time. The term "climate change" indicates a significant variation (in a statistical sense) in either the mean state of the climate or its variability for an extended period of time, usually decades or longer (Wilkinson 2006). In general, the studies described in this volume deal with the two different components of climate change: precipitation and temperature.
4. Here we refer to Anderson's (2006) estimates for Sub-Saharan Africa and South Asia based on PAGE 2002 (Policy Analysis of the Greenhouse Effect) (Hope 2006). The PAGE model (an IAM used extensively by *The Stern Review* [Stern 2007]) estimates future output and growth with and without climate change. Under the IPCC's Special Report on Emissions Scenarios (SRES) A2 climate-change scenario (in which global mean temperature increases by

- 3.9°C by 2100) (Nakićenović and Swart 2000), PAGE 2002 predicts that climate change in India and Southeast Asia and in Africa and the Middle East will cause GDP losses of about 2.5 percent and 1.9 percent, respectively.
5. The IPCC's SRES A2 scenario (Nakićenović and Swart 2000) might not accurately represent the expected GDP and population growth rates and the consequential emissions path. As a result, the A2 scenario is an extreme one that overestimates the negative impact that climate change will have on poverty reduction efforts.
  6. Autonomous adaptation is typically distinguished from planned adaptation, which refers to policy-based actions that are needed when market failures or other coordination problems hinder relevant collective responses to climate change.
  7. World Bank (2010) surveys private and public risk mitigation strategies in the face of natural hazards.

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## CHAPTER 2

# The Forecast for Poverty: A Review of the Evidence

Emmanuel Skoufias, Mariano Rabassa, and Sergio Olivieri

### Introduction

Given the complexities involved in analyzing the impacts of climate change on poverty, different approaches may be helpful. One is to use economywide growth models that incorporate consistent climate-change scenarios to show how climate change might affect the path of poverty over the next decades. Another approach is to learn about sector-specific channels (such as agricultural productivity) through which longer-term climate change affects poverty, the size of such impacts, the potential heterogeneity of those impacts, and the types of policies that may alleviate the adverse impacts. The information generated by this approach is useful in tackling poverty today and in preparing for future adaptation to climate change. Yet another approach is to explore how current climate variability affects poverty to predict the impacts of *increased* variability on future poverty.

This chapter reviews recent studies that have estimated the poverty-related and distributional impacts of climate change in these complementary directions. Given the multidimensional nature of welfare and the myriad ways in which climate change can affect the different dimensions of household well-being, we limit our discussion to monetary measures

(that is, consumption or income per capita), especially because these measures are used to calculate poverty rates. However, it is important to bear in mind that climate change may also have serious effects on health (an important dimension of welfare, which chapter 5 of this volume addresses further) and on ecosystem services (apart from agriculture)—both of which are difficult to measure monetarily.

The next section analyzes the potential effects of climate change on poverty from an aggregate perspective without considering the potential heterogeneity of impacts across the population.<sup>1</sup> The “Introducing Heterogeneity” section then describes analyses of the channels through which climate change will affect specific sectors of the population based on household-level data. The chapter concludes with key messages from this emerging literature as well as policy recommendations.

### **Climate Change and Global Poverty: The Aggregate Perspective**

Before reviewing the empirical literature, it is worth asking what is involved in predicting the poverty impacts of climate change using aggregate data. In general, such predictions require five pieces of information:

- The output-climate elasticity, which provides estimates of the percentage change in output due to a change in climate based on historical data and is useful for predicting the effect of future climate change on economic activity
- The poverty-output (or poverty-growth) elasticity, also based on historical data, which translates percentage changes in output per capita into changes in the poverty rate
- Estimated future climate change
- Estimated future trajectory of either gross domestic product (GDP) or income per capita in the absence of climate change
- Estimated population growth.

In general, the papers cited in this section differ regarding their estimates of these elasticities and the type of information they use for future projections.

#### ***Looking to the Past: Evidence from Cross-Sectional Historical Data***

A number of recent studies have opted for a “backward-looking” approach to analyze the effects of climate change on economic activity and ultimately on poverty. These studies, mimicking the approach emphasized in

the growth and development literatures, examine the relationship between climate and aggregate economic variables in cross-sections of countries or regions.

One advantage of this approach is that, by direct examination of aggregate outcomes, one can avoid relying on a priori assumptions about which mechanisms to include in the climate-economy interactions, how these mechanisms might interact, and ultimately how they influence macro-economic outcomes. Another advantage is that the use of cross-sectional data yields estimates of the long-run relationship between climate and aggregate output, taking into account historical adaptation.

For example, Dell, Jones, and Olken (2009) use cross-sectional data from 134 countries to examine how temperature affects GDP. Their output-climate elasticity estimate, based on historical data, reveals that each additional degree Celsius is associated with a statistically significant reduction of 8.9 percentage points of per capita GDP. The authors also provide evidence of this elasticity at the subnational level by considering the temperature-income relationship using municipal-level data for 12 countries in the Latin America and Caribbean region. Remarkably, they find that temperature *increases* correlate with income *decreases* within countries and even within states within countries.<sup>2</sup> However, they make no attempt to either simulate the impacts of the predicted temperature increase on income or to estimate its effect on poverty.

In a similar vein, Andersen and Verner (2010) examine the relationship between temperature and welfare at the municipality level within five countries in Latin America (Bolivia, Brazil, Chile, Mexico, and Peru). The coefficients of temperature (and temperature squared) provide an estimate of the long-run relationship between temperature and welfare (that is, the output-climate elasticity) inclusive of adaptation. The estimated relationships are then used to simulate the impact of the climate changes that the Intergovernmental Panel on Climate Change (IPCC) projects for the next 50 years (IPCC 2007a, 2007b).

The authors' poverty analysis, however, is crude. They do not attempt to estimate the poverty-output elasticity; they simply assume that a negative relationship exists between per capita income and poverty. As previously explained, income per capita and population growth projections are needed for more precise 50-year projections of the number of poor people. Therefore, the authors are careful to warn that their simulation results should not be interpreted as forecasts but as simply indicative of the direction and magnitude of the effects that might be expected from climate changes. Table 2.1 summarizes the estimated impacts of

**Table 2.1 Projected Income and Poverty Effects of Climate Change by 2060 from Municipality-Level Data in Selected Latin American Countries**

	<i>Effect of climate change on average incomes (percentage change)</i>	<i>Effect on poverty</i>	<i>Effect on inequality</i>
Bolivia <sup>a</sup>	2.9	Decrease	Decrease
Brazil	-11.9	Increase	Increase
Chile	-6.7	Increase	Neutral
Mexico	0	Neutral	Neutral
Peru	-2.3	Increase	Neutral

*Source:* Andersen and Verner 2010.

*Note:* Four explanatory variables are included in the regression models: temperature, rainfall, education, and urbanization rates. Temperature and rainfall estimates are based on 50-year IPCC projections (2008–58).

The estimates project changes relative to a baseline of no climate change, not relative to current conditions. a. In four of the five countries, the dependent variable in the analysis is income per capita, whereas in Bolivia, consumption per capita is used.

increased temperature on the mean level of welfare along with the *likely direction* of the effects of anticipated future climate change on poverty and income inequality.

A few points are worth highlighting: First, the presented estimates (derived from the country-specific elasticities and climate projections) refer to the percentage change in per capita income as a result of climate change relative to a world without it. Second, the direction of the poverty impact of climate change is derived by assuming a distribution-neutral change in the mean level of welfare. Third, as in the case of per capita income changes, the increase or decrease in poverty projects a situation relative to a world without climate change, not relative to the current situation. Therefore, a prediction that poverty will increase in Brazil does not imply that poverty will necessarily be higher relative to the present but that it will be higher in 2058 relative to the no-climate-change scenario. Finally, caution should be applied when looking at the reported effects on poverty and inequality because they are based on the distribution of income (per capita) among municipalities, not households.

Assunção and Chein Feres (2009) estimate the poverty impacts of climate change based on cross-sectional data at the municipality level in Brazil. They first estimate the impact of climate change on agricultural productivity (a proxy for the output-climate elasticity), measured as agricultural output per hectare in each municipality. Next, they use IPCC's temperature and rainfall projections for 2030–49 to build a different climate vector for each municipality, from which they obtain the percentage change in agricultural productivity induced by climate change. They

estimate that global warming will decrease the agricultural output per hectare in Brazil by 18 percent, with the municipality-specific estimates ranging from  $-40$  to 15 percent.

The authors explore the link between agricultural productivity and poverty by means of a cross-sectional regression of the poverty rate at the municipality level against the log of the agricultural output per hectare and the log of the total population in the municipality. Using instrumental variable methods to account for the correlation between agricultural output and the error term of the regression, they estimate that doubling agricultural productivity reduces poverty at the municipality level by 12.8 percentage points. Based on this estimate, they predict that climate change will increase the poverty rate in rural areas by 3.2 percentage points. Considering that the current poverty rate is 40 percent, the authors claim that the number of poor people in Brazilian rural areas will increase by 8 percent.

The estimates also reveal interesting geographical variations in the poverty impacts of climate change. Although the North region will be the most affected area in absolute terms (its rural poverty rate increasing by 6.2 percentage points), the South region is projected to benefit from a poverty rate *reduction* of 0.9 percentage points.<sup>3</sup>

To allow for more adaptation options than those considered by the simple Ricardian approach to estimating climate-change impacts on agricultural productivity, Assunção and Chein Feres (2009) consider two alternatives:

- First, they consider a measure of total poverty—taking into account all residents in each municipality (that is, including all urban households as well as rural households). This alternative measure of poverty captures the fact that some individuals might adapt to the new climate conditions by changing sectors or occupations.
- Second, they build a migration-adjusted poverty measure.<sup>4</sup> Using this adjusted sample, they compute a poverty measure for each municipality, for both urban and rural areas. After allowing for labor mobility across sectors or across municipalities, the absolute poverty-rate increase in rural areas goes down—from 3.2 percentage points (the earlier estimate, without accounting for labor mobility) to 2.0 percentage points.

In sum, these results suggest that climate change is likely to generate heterogeneous effects within Brazil, with poverty increasing in the

already poorer North and decreasing in the already richer South. Moreover, the poverty impacts of climate change are likely to be less severe depending on the extent to which households can adapt by migrating across municipalities or switching sectors of employment.

The major shortcoming of the Assunção and Chein Feres (2009) study is that it overstates the estimated impacts of climate change on poverty in Brazil because it does not take into account the potential increase in mean per capita income from economic growth over the next 40 years. In other words, the authors consider climate change as it would happen tomorrow, predicting the impact of a warming climate based on *today's* poverty rate instead of on the prevailing poverty rate in 2050 relative to a world without such a warming. The proper way to present poverty estimates associated with future climate change is to project both output and population growth and then use the elasticities to predict climate change's impact on poverty.

### ***Accounting for Future Growth: Evidence from Integrated Assessment Models***

An integrated assessment model (IAM) is a general equilibrium model that relies on microevidence to quantify various socioeconomic dimensions of climate change and then aggregates these to estimate a net effect on national income. IAMs are used extensively in the climate-change literature to model climate-economy interactions, and they form the basis of many policy recommendations regarding greenhouse gas (GHG) emissions control. The typical outputs of an IAM are the future trajectories of key economic variables—including GDP per capita with and without climate change—as well as income paths under different policy scenarios.<sup>5</sup>

***The PAGE model.*** The earliest IAM-based estimates of the impact of climate change on poverty, to our knowledge, are Anderson's (2006) estimates for Sub-Saharan Africa and South Asia based on PAGE 2002 (Policy Analysis of the Greenhouse Effect).<sup>6</sup> The PAGE model estimates future output and growth with and without climate change. Under the IPCC's Special Report on Emissions Scenarios (SRES) A2 climate-change scenario (Nakićenović and Swart 2000)—in which global mean temperature increases by 3.9°C by 2100—PAGE 2002 predicts that climate change in India and Southeast Asia and in Africa and the Middle East will cause GDP losses of about 2.5 percent and 1.9 percent, respectively, compared with what could have been achieved in a world without climate change.

Anderson converts these output and growth projections into poverty impacts by using regional poverty-output elasticity estimates, population forecasts, and two assumptions: (a) that average household income grows at 0.8 times the rate of GDP per capita<sup>7</sup> and (b) that the distribution of income remains constant. Based on these projections, the author reports that, by 2100, climate change could mean that up to 12 million more people in South Asia and 24 million more people in Sub-Saharan Africa will be living on less than \$2 a day.<sup>8</sup>

Although the poverty predictions are based on a highly aggregative and simplified model that does not take adaptation into account, the illustrative results suggest that climate change will negatively affect poverty. As *The Stern Review* (Stern 2007) rightly noted, these poverty impacts are likely to be smaller if aggregate growth in these countries and regions proceeds faster than what the IPCC's SRES A2 scenario assumes (including a high global population [15 billion] by 2100 and world GDP growth of 2 percent per year). In fact, recent GDP and population growth trends suggest that the A2 scenario's view has been pessimistic, and hence Anderson's poverty impacts might overestimate the actual impact.

***The RICE model.*** To update Anderson's estimates to more realistic projections, we model the long-term impacts of climate change on poverty using the Regional Integrated Model of Climate and the Economy (RICE) developed by Nordhaus (2010) under three scenarios:

- *Baseline* simulates a world without climate change.
- *Business as usual (BAU)* reflects the impact of current trends in economic growth and GHG emissions on the climate, estimating the impact of climate change on the overall economy without any emission abatement policies.<sup>9</sup>
- *Optimal abatement* is based on Nordhaus's calculation of an emission abatement path with full participation by all countries that maximizes global intertemporal economic welfare.

We translate the implications for poverty of these different growth scenarios by using historical estimates of growth-poverty elasticities (for the full dataset, see annex 2A).<sup>10</sup> Table 2.2 summarizes the main impacts of climate change on global poverty under the three scenarios.

Under the baseline (no climate change) scenario, the model projects an annual global real per capita output growth rate of 2.2 percent up to 2055.<sup>11</sup> This outcome contributes to cutting the world poverty rate

**Table 2.2 Three Scenarios for Climate-Change Impacts on World Poverty, 2005–55**

<i>Scenarios</i>	<i>Number of poor people (millions)</i>			<i>Headcount poverty rate (%)</i>		
	<i>2005</i>	<i>2055</i>	<i>Change</i>	<i>2005</i>	<i>2055</i>	<i>Change</i>
Baseline <sup>a</sup>	2,069.4	1,259.1	(810.3)	32.3	14.1	(18.2)
BAU <sup>b</sup>	2,069.4	1,269.2	(800.2)	32.3	14.2	(18.1)
Different from baseline	0	10.1	10.1	0	0.12	0.12
Optimal abatement <sup>c</sup>	2,069.4	1,268.5	(800.9)	32.3	14.2	(18.1)
Different from BAU	0	(0.7)	(0.7)	0	(0.01)	(0.01)

*Source:* Authors' estimates based on the RICE model of Nordhaus 2010.

*Note:* Business as usual (BAU) scenario is a continuation of current trends without emission abatement. Poverty is defined as income per capita of \$2 a day or less in 2005 purchasing power parity (PPP) terms. The use of parentheses designates negative numbers.

a. The baseline scenario (no climate change) projects annual world per capita gross domestic product (GDP) growth of 2.2 percent until 2055.

b. The BAU scenario (current climate-change trends with no GHG emission abatement) projects annual world GDP growth of 1.5 percent less than the baseline.

c. The optimal abatement scenario (maximized emission-abatement participation worldwide) projects annual world GDP growth of 1.25 percent less than the baseline.

(per capita income of \$2 a day or less) by more than half—from 32.3 percent in 2005 to 14.1 percent by 2055. Under the RICE model's BAU scenario (climate damage along the current trajectory), world GDP growth in 2055 would be 1.5 percent lower than in the baseline (amounting to 2.167 percent).

Under the BAU scenario, the estimated number of poor in 2055 would be modestly higher (by about 10 million) than under the no-climate-change scenario, with most of the additional poor living in Africa and South Asia. It is worth stressing that this analysis focuses on the expected or mean value of the probability distribution of damage from climate change. Obviously, looking at more extreme outcomes (a lower probability) would increase the estimates for GDP losses and poverty.

Under the optimal abatement scenario, the extra number of people in poverty due to global warming in 2055 is projected to be only slightly lower (about 9 million) because the effects of global GHG emission abatement on aggregate economic damages necessarily accrue more to higher-income countries. Unlike adaptation strategies, emissions mitigation does not specifically target the poor. The major gains in poverty averted by following the optimal abatement strategy would indeed occur on a longer time horizon—by 2100 and beyond.

Even though the aggregate impacts of climate change on poverty seem to be modest by mid-century, the findings do not imply that the impacts will be equally distributed among the population. To analyze how climate change will affect specific population sectors, one must use

household-level data and explicitly model the channels through which future warming will affect economic activity.

### **Introducing Heterogeneity: The Microeconomic Approach**

The discussion so far has relied on the evidence emerging about the relationship between climate (temperature and precipitation) and growth (or GDP) in a cross-section or panel of countries or municipalities within selected countries. Although informative, these studies shed no light on the channels through which climate change can affect household welfare. For example, climate change may reduce agricultural productivity and also negatively affect poor people's livelihoods through its effects on health, access to water and other natural resources, and infrastructure. Considering the complexities involved in modeling some of these channels, the literature has focused largely on the poverty impacts related to agricultural output, and this section reviews those quantitative estimates.

Over the past few years, a large literature has attempted to quantify the impacts of climate change on agricultural productivity at the regional and country levels.<sup>12</sup> The general consensus emerging from this literature is that climate change will negatively affect agricultural productivity and yields and that the impacts will vary both across countries and within countries. To the extent that yield changes are good predictors of the changes in rural household welfare—and ultimately of the changes in poverty rates, at least in rural areas—these findings suggest that climate change would significantly affect poverty rates. Yet the impacts on agricultural yields may actually be a rather poor predictor of the impacts on poverty.

A variety of mediating factors, including the following, can mitigate the impacts on household welfare as well as the distribution of these impacts across different households:

- The extent of autonomous adaptation by households, such as the ability to migrate or switch employment between agricultural and nonagricultural occupations
- The extent of policy-induced adaptation through prices and explicit government programs, such as access to credit and insurance<sup>13</sup>
- The distribution of productive endowments (such as irrigated and non-irrigated land or skilled and unskilled labor)
- The dual role of rural households as consumers and producers of food—and whether they are net consumers or net producers.

Economic growth—often absent in discussions of the future impacts of a warming world—will have a tremendous ameliorating effect as food expenditures decrease as a share of total expenditures and as the agriculture sector decreases as a share of national GDP (Nordhaus 1993).

### **General Equilibrium Modeling**

Hertel, Burke, and Lobell (2010) analyzed the impacts of climate change through a more careful modeling of the channels and heterogeneity of impacts in the context of economic growth. They use disaggregated data on household economic activity (stratified by primary source of income) within 15 developing countries and a general equilibrium global trade model (the Global Trade Analysis Project, or GTAP) to explore how changes in agricultural productivity will affect poverty in poor countries. Although their model allows for only limited heterogeneity, a key feature is that it allows different types of households to be affected differently by the prices of agricultural goods.<sup>14</sup>

The authors use three scenarios of how climate change affects agricultural productivity (low, medium, or high productivity) to evaluate the resulting changes by 2030 in global commodity prices, national economic welfare, and poverty headcount rate (the portion of a nation's population living on less than \$1 a day).<sup>15</sup> The poverty consequences of a decline in agricultural productivity are evidenced through two channels: *changes in earnings* and *changes in the real cost of living at the poverty line*.

The impact of a food price rise on earnings depends on the income sources for a given household group (estimated from household survey data). If earnings rise faster than the cost of living for households at the poverty line in a given socioeconomic stratum, the poverty headcount falls and vice versa. The responsiveness of the stratum poverty headcount to a given real income shock is determined by the density of the stratum population in the neighborhood of the poverty line (also estimated from the household survey data). When combined with information about the distribution of national poverty across socioeconomic strata, the authors can estimate the change in the national poverty headcount.

A number of interesting findings emerge from this modeling effort:

- Large changes in grain prices do not translate into large changes in the cost of living<sup>16</sup> because consumers adjust their consumption bundle to account for the new pattern of prices, and staple grains are only one part of total consumption. “While world prices for staple grains rise by an average of more than 30% in the low productivity scenario, the

average impact on the real cost of living at the poverty line is more modest—just 6.3%” (Hertel, Burke, and Lobell 2010).

- The portion of the poverty change driven by cost-of-living changes is largest for the urban wage labor household stratum. (The cost-of-living change is the product of the percentage change in the real cost of living at the poverty line and the stratum-specific elasticity of poverty with respect to real income.) This is because the density around the poverty line in the urban wage labor household stratum is relatively high. In contrast, the agriculture-dependent households show the smallest change.<sup>17</sup>
- In the “low productivity” scenario (higher temperature), rising world commodity prices translate into increased returns to factors employed in agriculture. Consequently, earnings increase sharply and the poverty rate drops among the agricultural self-employed households. On the other hand, poverty rises among the nonagricultural specialized households because their earnings fall given the *relative price decline* of nonagricultural commodities compared with agricultural goods. Under the “high productivity” scenario, these results are reversed, with no apparent effect on poverty for the medium-climate-change scenario.
- The combined poverty impacts on agricultural self-employed households are positively correlated with the size of the productivity shock—with lower global productivity generating higher agricultural prices and reduced poverty among these households. The opposite is true of the nonagricultural self-employed households. The net change in national poverty depends on the contribution of each stratum to overall poverty.

In sum, the overall (and by stratum) poverty changes across all countries for the low-productivity climate-change scenario show that, in nearly all countries, poverty increases in some strata and decreases in others. The notable exceptions are most African countries, where the yield impacts of climate change are severe and no single stratum experiences significant poverty reductions.

The Hertel, Burke, and Lobell (2010) study provides a promising approach for studying the impacts of climate change, taking into account general equilibrium effects between agricultural productivity, cost of living, and earnings. However, as in most models, there are serious trade-offs between the tractability of the general equilibrium effects and the heterogeneity incorporated into the model.

### ***Heterogeneity Galore***

The study by Jacoby, Rabassa, and Skoufias (2011) applies a flexible framework for quantifying the distributional impacts of climate change in rural economies. In this study, focusing on India, welfare is measured by consumption per capita and is modeled based on the households' resource endowments (such as land and labor) and the returns from farm and nonfarm activities. The authors introduce more heterogeneity into the model by distinguishing between the type of land owned by households (irrigated and nonirrigated) and type of labor (skilled and unskilled). Each of these endowments may have different returns and responses to climate.

Using a comparative statics framework, the impacts of climate change on household consumption can be expressed as the impact of changes in temperature on the returns to land (a summary measure of agricultural productivity) multiplied by (a) the proportion of income derived from owned land; (b) the impacts of temperature on the returns to labor multiplied by the proportion of income derived from labor; and (c) the impacts of climate change on the price of food multiplied by the net consumption ratio (that is, the value of the net marketed surplus of food by the household).<sup>18</sup>

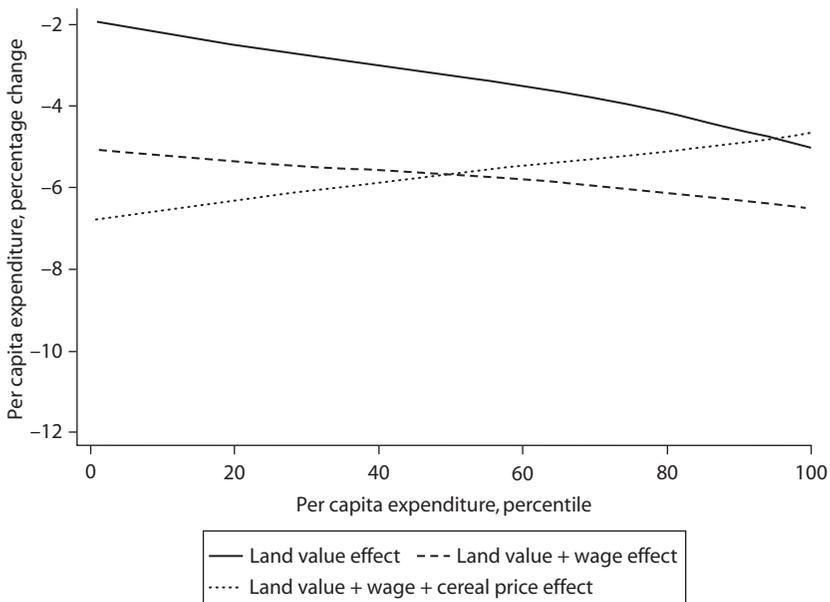
Using microdata representative for all India and following the Ricardian approach proposed by Mendelsohn, Nordhaus, and Shaw (1994), the authors estimate the impacts of climate change in 2040 on agricultural productivity and wages, taking into account adaptation (using district-level cross-sectional data) and assuming imperfect mobility of labor.<sup>19</sup> They also estimate the impacts of climate change on agricultural productivity in the absence of adaptation, using panel data at the district level (Deschenes and Greenstone 2007). Combining these estimates of the impacts of climate change on the returns to land and labor with the household-specific information on endowments of land and labor, they derive household-specific impacts of the climate change on consumption, which is a prerequisite for a proper distributional analysis.<sup>20</sup>

The main results of the Jacoby, Rabassa, and Skoufias (2011) study are as follows:

- The substantial fall in agricultural productivity (17 percent overall inclusive of adaptation) that is predicted as a result of warming by 2040 will translate into a much more modest consumption decline (of 6 percent on average) for most households. This is because these households derive the bulk of their income from wage employment, and (rural) wages are estimated to fall by only a third as much as agricultural productivity. The same general pattern is observed in the case of no adaptation.<sup>21</sup>

- Climate change will have heterogeneous impacts across geographical areas and across the income distribution, as shown in figure 2.1. Ignoring cereal price effects, climate change appears to have a progressive effect because wealthier households suffer proportionally greater consumption losses. A household in the top percentile of the per capita expenditure distribution would experience a decline in consumption nearly 2 percentage points greater than a household in the bottom percentile. This progressivity is driven by the skewed land distribution and the fact that larger landowners are concentrated in the higher percentiles. By contrast, temperature-induced wage declines are relatively more costly to the poor than to the rich, mainly because the poor tend to engage in climate-sensitive agricultural employment.
- Once the welfare effects of rising cereal prices are taken into account, climate change impacts are regressive, falling more heavily on the poor than the rich. This is true in both urban areas (where it is

**Figure 2.1 Climate-Change Incidence Curves for Rural Population in India, 2040**



Source: Jacoby, Rabassa, and Skoufias 2011.

Note: In the figure, following a baseline Ricardian approach, the warming projection for 2040 is based on a Hadley Centre Coupled Model, version 3 (HadCM3 model) (IPCC 2001). The curves assume a 17 percent decline in agricultural productivity from a projected 1.25°C temperature increase for the country as a whole by 2040, although there is spatial variability on the projected changes in temperature.

assumed that cereal price effects are the only welfare consequence of climate change) and rural areas (where the beneficial impact of higher prices to agricultural producers offsets the decline in land productivity).

Although the model employed by Jacoby, Rabassa, and Skoufias (2011) is primarily equipped for estimating the distributional rather than the poverty impacts of climate change, the effects on poverty can be predicted with the help of some additional assumptions. As discussed previously, in estimating the poverty impacts of climate change, it is important to take into account the growth in the economy over time and the associated decline in the share of food in household consumption.

Table 2.3 underscores the importance of this point by estimating the poverty rates in 2040 assuming different annual growth rates in the average standard of living. Even with very low growth in mean consumption (equal to the 1951–90 average growth rates in mean consumption in India), the urban poverty rate in the presence of climate change is likely to be less than half (15.7 percent) what the urban poverty rate would have been without any growth (32.3 percent).<sup>22</sup>

Taking into account average income growth up to 2040, the national poverty rate will rise by 3.5 percentage points compared with the counterfactual of zero warming (see table 2.4). Given the current population projections, climate change is predicted to result in around 50 million more poor people than there otherwise would have been in that year.

**Table 2.3 Projected Impact of Climate Change on Poverty Rates under Three Growth Scenarios in India, 2004–40**

percent

	<i>Base year</i> 2004/05	<i>No growth</i> 2040	<i>Low growth<sup>a</sup></i> 2040	<i>Medium growth<sup>b</sup></i> 2040	<i>High growth<sup>c</sup></i> 2040
Rural	48.8	54.8	35.8	18.3	2.1
Urban	31.1	32.3	15.7	5.8	0.2
All	44.5	49.4	31.0	15.3	1.1

*Source:* Jacoby, Rabassa, and Skoufias 2011, using annual mean consumption growth rates (from National Sample Surveys) drawn from Datt and Ravallion 2011.

*Note:* The poverty rate is defined using the official state-level poverty lines of 2009. The warming projection for 2040 is based on the HadCM3 model (IPCC 2001), projecting a 1.25°C temperature increase for the country as a whole by 2040, although there is spatial variability on the projected changes in temperature.

a. Low growth = annual average mean consumption growth in India for 1958–91 (0.58 percent rural, 0.79 percent urban).

b. Medium growth = annual average mean consumption growth for 1991–2006 (1.17 percent rural, 1.49 percent urban).

c. High growth = double the rate of the medium growth scenario (2.34 percent rural, 2.98 percent urban).

**Table 2.4 Projected Impact of Climate Change on Poverty Rates under Three Growth Scenarios in India by 2040***percentage points*

	<i>Low growth<sup>a</sup></i>	<i>Medium growth<sup>b</sup></i>	<i>High growth<sup>c</sup></i>
Rural	5.9	4.4	0.7
Urban	1.1	0.6	0.1
All	4.8	3.5	0.6

*Source:* Jacoby, Rabassa, and Skoufias 2011.

*Note:* Poverty rate changes are relative to a no-climate-change scenario, not to current trends. The poverty rate is defined using the official state-level poverty lines of 2009. The warming projection for 2040 is based on the HadCM3 model (IPCC 2001), projecting a 1.25°C temperature increase for the country as a whole by 2040, although there is spatial variability on the projected changes in temperature.

a. Low growth = annual average mean consumption growth in India for 1958–91 (0.58 percent rural, 0.79 percent urban).

b. Medium growth = annual average mean consumption growth for 1991–2006 (1.17 percent rural, 1.49 percent urban).

c. High growth = double the rate of the medium growth scenario (2.34 percent rural, 2.98 percent urban).

### ***The Impacts of Increased Climate Variability on Welfare and Poverty***

Although there is a great deal of uncertainty over the exact magnitudes of the global changes in temperature and especially precipitation, it is widely accepted that significant deviations of climate variability from its historical patterns are likely (IPCC 2007b). Erratic weather and increased climatic variability will affect agricultural productivity, which—depending on how effectively urban and rural households have employed risk-management strategies before and after the fact—may translate into reduced income and reduced food availability at the household level.

Numerous studies have examined the impacts of natural disasters and extreme weather-related shocks on different dimensions of welfare (see Baez and Mason 2008; World Bank 2010a for a thorough review of this literature). In general, they show that extreme weather events are likely to negatively affect agricultural incomes (and thus food; basic nonfood consumption; and investments in human capital, health, nutrition, and productive physical assets). Many of these studies, however, tend to rely on the respondents' perceptions about the incidence of different types of shocks, or they use rainfall and temperature data as tools (for example, as instrumental variables) to analyze how shocks to income affect other outcomes, such as consumption or investments in human capital.<sup>23</sup> Hardly any studies use actual weather data to analyze the general relationship between weather and the level of welfare.

In chapter 4 of this volume, Skoufias and Vinha examine whether climatic variability—namely, deviations of rainfall and temperature from their long-run means—significantly affect the average well-being of rural

households in Mexico. They report that the timing of the rainfall or temperature shock makes a substantial difference in its estimated impact on welfare. For example, per capita expenditures are 14 percent higher if the prior agricultural year (October to September) was at least one standard deviation drier than the average of a previous 35-year period (1951–85). However, if the rainfall shock were to occur during the wet season of that same year (April to September), neither positive nor negative rainfall shocks appeared to significantly affect household per capita expenditures.

Also using such insights, in chapter 3, Skoufias, Essama-Nssah, and Katayama use data from rural Indonesia to consider the effects of two rainfall-related shocks: (a) a delay in the onset of monsoon and (b) a significant shortfall in the amount of rain in the 90-day postmonsoon period. Focusing on households with family farm businesses, they find that rice-farm households in areas experiencing low rainfall following the monsoon's onset are negatively affected: such a shortfall is associated with a 14 percent reduction in the households' per capita expenditures. Moreover, rice-farming households manage to protect their food expenditures in the face of weather shocks at the expense of nonfood expenditures. The findings regarding the impacts of climatic variability on nonfood consumption expenditures are consistent with households' reduction of expenditures on health and education—reductions that ultimately may have a longer-term effect on poverty by reducing investment on the human capital of children.

The Indonesia study also sheds light on some potential policy instruments that might moderate the welfare impacts of climate change. Access to credit and public works projects in communities can help households cope with shocks and thereby play a strong role in protection from weather-related shocks. This is an important consideration for the design and implementation of adaptation strategies.

***Potentially large poverty increases.*** The preceding studies focus on how weather-related shocks affect the mean level of welfare, though not necessarily poverty. The negative effects on welfare suggest that the current risk-coping mechanisms have a limited capacity in protecting welfare from erratic weather patterns. Considering that coping mechanisms are backward looking (in the sense that they develop over time based on weather variability observed over very long periods of time), there is a concern about the extent to which such mechanisms can adjust to the changes in climatic variability predicted over the next 50 to 90 years. All in all, these observations imply that the predicted changes in climatic variability patterns are likely to reduce the effectiveness of the current

coping mechanisms even more and thus increase household vulnerability and poverty further.

Ahmed, Diffenbaugh, and Hertel (2009) is the only study to date making an effort to model the channels and estimate the poverty impacts of extreme weather events such as extreme heat, droughts, and floods. They apply the GTAP comparative static computable general equilibrium model (practically identical to that in Hertel, Burke, and Lobell [2010], discussed above) to 16 countries. The two studies differ mainly regarding the origin of the shocks to agriculture, which Ahmed, Diffenbaugh, and Hertel (2009) derive from three sources:

1. The percentage of annual total precipitation from events exceeding the 95th percentile in the 1961–90 period
2. The maximum number of consecutive dry days
3. The heat wave duration index.

The authors compare two 30-year periods a century apart (1971–2000 and 2071–2100) in the simulations under the IPCC's A2 scenario.<sup>24</sup> All 16 countries exhibit substantial increases in the occurrence and magnitude of extreme heat events, with the occurrence of the present 30-year-maximum event increasing by more than 2,700 percent in parts of the northern Mediterranean and the magnitude of the 30-year-maximum event increasing by 1,000–2,250 percent (or even more) in much of central Africa. Most countries also display increases in the occurrence and magnitude of extreme dry events, with peak changes of greater than 800 percent and 60 percent, respectively, occurring over Mediterranean Europe.

The magnitude and spatial heterogeneity of changes in climate volatility suggest that the impacts on poverty could also be large and heterogeneous. Among the 16 countries analyzed, those with the highest shares of populations entering poverty because of these extreme events include Bangladesh, Malawi, Mexico, Mozambique, Tanzania, and Zambia. For example, in Malawi and Zambia, a simulated 75 percent decline in grains productivity causes the poverty headcount to increase by about 7 percentage points relative to the countries' total populations.

***Greater vulnerability of urban populations.*** There is also tremendous heterogeneity in the poverty vulnerability across different population segments (differentiated by primary income source). As in Hertel, Burke, and Lobell (2010), the analysis reveals that the most vulnerable group is the urban wage-labor-dependent stratum. Although the urban labor group contributes modestly to total poverty in the sample of 16 countries, it

appears to be highly vulnerable to extreme climate events (in Malawi, for example, the poverty rate for this group doubles). Mexico and Zambia also show high vulnerability in this group.

The source of vulnerability of the urban poor is their extreme exposure to food price increases. (With food being a major expenditure, this group's consumption falls with rising prices, pushing them below the poverty threshold of consumption.) Agricultural households, on the other hand, are much less exposed: as consumers, they are generally hurt by the adverse productivity shock, but as producers, they also tend to benefit from the higher food prices.

Given that the shares of developing countries' populations living in rural areas are projected to decrease by more than one-third between 2010 and 2050 (UN 2009), climate extremes may increasingly affect national-scale poverty in the future because of higher population concentrations in the more-sensitive urban strata.

***Risk management for rural populations.*** The poverty impacts estimated above are based on simple approximations of how extreme climate events influence poverty by affecting agricultural productivity and raising prices of staple foods. However, it is important to bear in mind that an extensive literature also documents an association between weather variability (in the absence of credit and insurance markets) and a set of risk management strategies (before and after the fact) by rural households aimed at protecting household welfare.

For example, rural households may undertake income-smoothing strategies, such as the following, before the fact to spread the effects of weather-induced shocks through difficult times:

- Adopt low-return, low-risk crop and asset portfolios (Rosenzweig and Binswanger-Mkhize 1993)
- Draw upon savings (Paxson 1992)
- Take loans from the formal financial sector (Udry 1994)
- Sell assets (Deaton 1992)
- Diversify the occupations held by the adult members of the household (Menon 2009).

Additional strategies include the management of income risk through after-the-fact adjustments to supplement income, such as the following:

- Sending children to work instead of school (Jacoby and Skoufias 1997)

- Holding multiple jobs
- Engaging in other informal economic activities (Kochar 1999; Morduch 1995).

These risk management strategies themselves are associated with increased poverty and lower investment and growth (poverty traps) because poor households that are credit constrained will choose activities that reduce income variability but that also generate lower expected incomes than the activities chosen by wealthier (less constrained) households (Elbers, Gunning, and Kinsey 2007).

### **Key Messages and Policy Considerations**

Although the studies surveyed are quite heterogeneous in terms of data (country-level versus household-level data and cross-sectional versus panel data); methods (partial equilibrium versus computable general equilibrium); and focus (regional versus country-specific), a number of messages can be extracted.

#### ***Mitigating Effects of Economic Growth Are Often Ignored***

Most estimates of the poverty impacts of climate change tend to ignore the effect of aggregate economic growth on poverty and household welfare. Thus, many of them provide unduly pessimistic, if not unrealistic, scenarios. However, it is also important to bear in mind that the extent to which developing countries can sustain the high growth and the associated large poverty reduction rates of the recent past depends critically on whether they can maintain high growth rates while also burning less fossil fuel.

#### ***Climate Change Will Slow, but Not Reverse, Global Poverty Reduction***

Climate change will slow the pace of global poverty reduction, but—based on the mean or expected value of climate damages used in mainstream analyses such as Nordhaus’s (2010) RICE model or *The Stern Review* (Stern 2007)—the expected poverty impact will be relatively modest and far from reversing the major decline in poverty that is expected to occur over the next 40 years as a result of continued economic growth. However, some qualifications are in order:

- Much of the poverty impact is expected to be concentrated in Africa and South Asia, both of which would see more substantial increases in poverty relative to a baseline without climate change.

- The occurrence of less-probable but more extreme climate damage scenarios would naturally result in larger poverty increases.
- Aggregate projected damages are relatively low over the time horizon (mid-century) analyzed here. As climate change continues to unfold during this and the next century, aggregate damages could be substantial and have a larger effect on poverty.

### ***For the Full Story, Take Heterogeneity into Account***

The estimated impacts of climate change on agricultural yields are generally poor predictors of the poverty impacts of climate change at the national level. The studies reviewed here suggest that the decline in agricultural productivity resulting from climate change translates into much smaller poverty increases at the national level, primarily because of these two factors:

- Heterogeneity in how climate change affects different geographical areas within countries as well as across the national income distribution
- Heterogeneity in the households' ability to adapt: for example, moving across space and across sectors of employment.

It is important to keep in mind that the heterogeneity of climate-change impacts across space is not synonymous with heterogeneity in the ability of households to adapt (before or after the fact) to the climate changes.

### ***Regressive Impacts Will Hurt the Urban Poor the Most***

It also appears that the impacts of climate change are generally regressive—that is, falling more heavily on the poor than on the rich. However, the higher food prices associated with the global increase in temperatures are likely to hurt households that are net *consumers* of food and to benefit those that are net *producers* of food.

Moreover, increasing urbanization suggests that the number of net consumers of food is likely to increase substantially over the next few decades. This suggests that both results of climate change—gradual global warming and the increased incidence of extreme weather—are likely to hurt households dependent on urban wage labor much more than those dependent on rural labor (that is, those self-employed in agriculture).

Although uncertainty abounds about whether the global decline in agricultural productivity will translate into large increases in grain prices, some evidence indicates that price increases on the order of 30 percent by 2030 will translate into considerably smaller changes in the cost of living for those households close to the poverty line.

### ***Mitigation and Adaptation Policies Also Foster Growth***

Fortunately, many of the policies that can effectively reduce the impacts of climate change on poverty are the same strategies that promote sound development, poverty reduction, and economic growth. The most important policy elements are these:

- Enhancement of international trade to smooth the price impacts of regional or country-specific climate shocks
- Investment in human capital to increase employment opportunities for the poor
- Facilitation of migration to help the poor reach areas with better economic opportunities
- Provision of access to credit and developing insurance markets
- Investment in transportation and communication infrastructure
- Investment in irrigation and water management to deal with extreme precipitation events
- Investment in adaptive agricultural research and in information and extension services
- Improvement of common-pool natural resource governance
- Creation of well-targeted, scalable safety-net systems.

The regressive impacts of climate change mentioned above, combined with the emerging evidence that access to social protection and credit programs moderate the welfare impacts of climate change, suggest that the establishment of safety-net programs and the strengthening of the institutions needed to implement and scale up such programs should be a critical component of country-level adaptation strategies.

In particular, countercyclical safety-net systems such as conditional and unconditional cash transfers; workfare programs (for example, food-or cash-for-work); and social funds (community-level programs in infrastructure, social services, training, and so on) can have immediate payoffs because they enable countries to deal with economic crises and other shocks that may not be related to climate change and climatic variability.

## Annex 2A Using the RICE Model to Estimate Poverty Impacts of Climate Change

### Methodology

To project the impacts of climate change on poverty, it is necessary to estimate (a) how climate change will affect the welfare measure (for example, per capita gross domestic product [GDP], per capita private consumption expenditure [PCE] from national account statistics, or household mean income); and (b) how these changes in welfare measures translate into poverty numbers.

Focusing on the second relation, a simple and straightforward concept is the poverty-growth elasticity. This relationship is derived from the fact that any poverty measure, such as the headcount ratio, can be expressed (for a given poverty line) as a function of the mean of the distribution and the parameters of the Lorenz curve<sup>25</sup>:

$$H = L_p^{-1} \left( \frac{z}{\mu}, \pi \right), \quad (2A.1)$$

where  $H$  is the headcount index;  $z$  is the poverty line;  $m$  is the mean of the distribution;  $L$  is the Lorenz curve for a given distribution, and  $p$  is a vector of parameters associated to  $L$ .

Differentiating the previous equation with respect to time, we obtain the dynamic counterpart:

$$\frac{dH}{H} = \frac{L_{pp}^{-1} z}{L_p^{-1} \mu} \frac{d\mu}{\mu} + \frac{L_{p\pi}^{-1}}{L_p^{-1}} d\pi, \quad (2A.2)$$

which shows how changes in poverty relate either to economic growth or to changes in the Lorenz curve. The first term on the right-hand side, also known as the growth component, can be estimated with a regression of the proportionate changes in poverty on the proportionate changes in the welfare measure, with or without controls ( $X$ ):

$$\frac{dH}{H} = \alpha - \beta \frac{d\mu}{\mu} + X\gamma + \varepsilon, \quad (2A.3)$$

where  $b$  is the poverty-growth elasticity with respect to the mean consumption given by  $m$ .<sup>26</sup>

For consistency, we replace the household mean income or consumption with the per capita PCE in the estimation of the parameter of interest. This empirical decision was made because projections from the Regional Integrated Model of Climate and the Economy (RICE) are available only for PCE per capita.

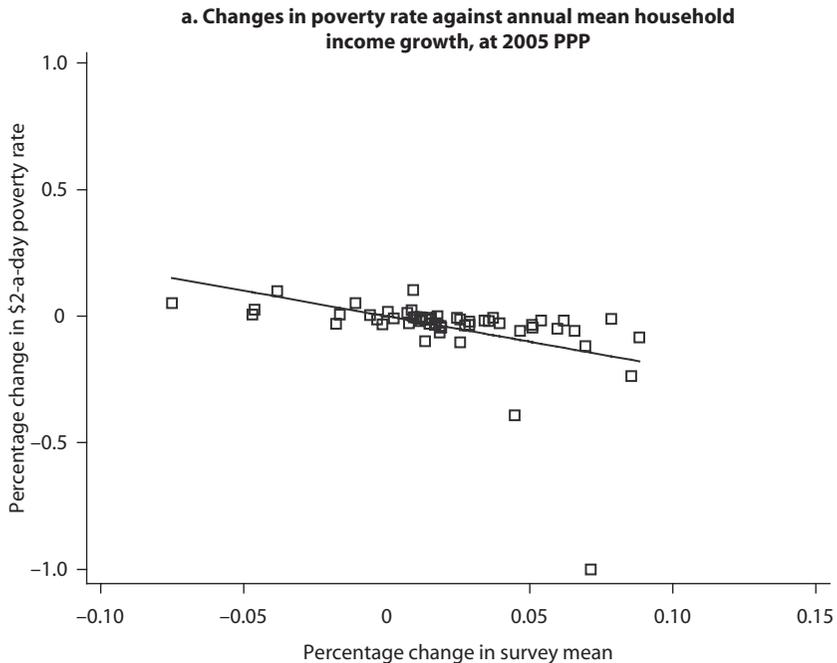
There exist differences between estimating the poverty-growth elasticity based on household mean income and estimating it based on per capita PCE. Panel a of figure 2A.1 shows the proportionate changes in the poverty rate against the average income growth rate. The overall poverty-growth elasticity (defined as \$2 a day at purchasing power parity [PPP]) is  $-2.02$  with a (heteroskedasticity corrected) standard error of  $0.82$ .

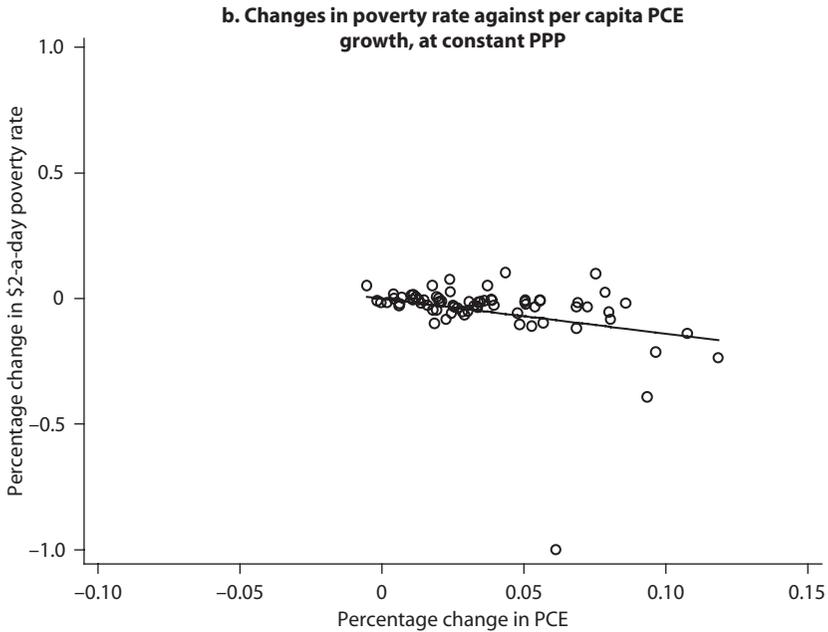
In contrast, panel b of figure 2A.1 plots the proportionate changes in the same poverty rate against the growth rate in PCE per capita. Though similar, the estimated elasticity of  $-1.44$  (standard error of  $0.60$ ) is not as strong as before.<sup>27</sup> It is important to note that these estimations are based on the same countries and time spells to make both welfare measures comparable across both space and time.<sup>28</sup>

**Data**

The data requirement for this exercise might be divided into two: historical data and projections. Historical data are needed to compute the

**Figure 2A.1 Changes in Poverty Headcount Ratio**



**Figure 2A.1** (continued)

*Source:* Authors' estimations based on data from World Bank 2010b and PovcalNet, the online tool for poverty measurement developed by the Development Research Group of the World Bank (<http://econ.worldbank.org/povcalnet>).

*Note:* Poverty is defined as per capita income of \$2 a day or less. PCE = personal consumption expenditure, PPP = purchasing power parity.

poverty-growth elasticity. For this purpose, we construct a dataset with the following variables: poverty measure (\$2-a-day headcount ratio), household mean income or expenditure, and per capita PCE. Our dataset includes 91 countries, 75 of which have at least two surveys from the early 1990s until 2000 (last year available). Table 2A.1 lists the countries and survey dates used in the simulation.

Following Ravallion and Chen (1997), we define a “spell” as the maximum distance between two surveys for one country within the time range defined in table 2A.1. We restrict the sample of countries' poverty measure and mean income (or expenditure) to those years that were computed over the same measure of living standards and area. In some cases, different subperiods use different measures for a given country; for instance, surveys may switch from income to consumption or extend the survey sample from urban to country representativeness.<sup>29</sup> Given that we are computing poverty-growth elasticities based on PCE, we complete

**Table 2A.1 Coverage of the Dataset for Poverty-Growth Elasticity Simulations**

<i>Region</i>	<i>Country</i>	<i>Survey dates</i>		<i>Welfare indicator</i>	<i>Region</i>	<i>Country</i>	<i>Survey dates</i>		<i>Welfare indicator</i>
European Union	Czech Republic	1993	1996	Income	Africa	Algeria	1995	—	Expenditure
	Hungary	1998	2004	Expenditure		Benin	2003	—	Expenditure
	Poland	1992	2005	Expenditure		Botswana	1994	—	Expenditure
	Slovak Republic	1996	—	Income		Burkina Faso	1994	2003	Expenditure
	Turkey	1994	2006	Expenditure <sup>a</sup>		Cameroon	1996	2001	Expenditure
Russia	Russian Federation	1993	2007	Expenditure <sup>a</sup>	Cape Verde	2001	—	Expenditure	
					Central African Republic	2003	—	Expenditure	
					Comoros	2004	—	Expenditure	
					Congo, Rep.	2005	—	Expenditure	
					Egypt, Arab Rep.	1991	2005	Expenditure	
EurAsia	Albania	1997	2005	Expenditure	Ethiopia	1995	2005	Expenditure	
	Armenia	1996	2007	Expenditure <sup>a</sup>	Guinea	1991	2003	Expenditure	
	Azerbaijan	1995	2005	Expenditure	Guinea-Bissau	1991	2002	Expenditure	
	Belarus	2000	2005	Expenditure	Gabon	2005	—	Expenditure	
	Bosnia and Herzegovina	2004	2007	Expenditure <sup>a</sup>	Kenya	1992	2005	Expenditure	
	Bulgaria	1994	2003	Expenditure	Lesotho	1993	2003	Expenditure	
	Croatia	1998	2005	Expenditure	Madagascar	1993	2005	Expenditure	
	Estonia	1995	2004	Expenditure	Malawi	1998	2004	Expenditure	
	Georgia	1996	2005	Expenditure	Mali	1994	2006	Expenditure	
	Kazakhstan	1996	2003	Expenditure	Mali	1994	2006	Expenditure	
	Kyrgyz Republic	1993	2004	Expenditure	Mauritania	2000	—	Expenditure	
	Latvia	1998	2007	Expenditure <sup>a</sup>	Morocco	1991	2007	Expenditure	
	Lithuania	1996	2004	Expenditure	Mozambique	1997	2003	Expenditure	
	Macedonia, FYR	1998	2006	Expenditure <sup>a</sup>					

*(continued next page)*

**Table 2A.1** (continued)

<i>Region</i>	<i>Country</i>	<i>Survey dates</i>		<i>Welfare indicator</i>	<i>Region</i>	<i>Country</i>	<i>Survey dates</i>		<i>Welfare indicator</i>
	Moldova	1997	2004	Expenditure		Namibia	1993	—	Income
	Romania	1998	2007	Expenditure <sup>a</sup>		Niger	2005	—	Expenditure
	Slovenia	1998	2004	Expenditure		Senegal	1991	2005	Expenditure
	Tajikistan	1999	2004	Expenditure		South Africa	1993	2000	Income
	Ukraine	1996	2008	Expenditure <sup>a</sup>		Swaziland	1995	2001	Expenditure
						Tanzania	1992	2000	Expenditure
India	India-Urban	1994	2005	Expenditure		Tunisia	1990	2000	Expenditure
	India-Rural	1994	2005	Expenditure		Uganda	1992	2005	Expenditure
						Zambia	1991	2004	Expenditure
Middle East	Iran, Islamic Rep.	1990	2005	Expenditure	Latin				
	Jordan	1992	2006	Expenditure	America	Argentina-Urban	1996	2006	Income
						Belize	1995	—	Income
						Bolivia	1991	2007	Income <sup>a</sup>
China	China-Urban	1990	2005	Expenditure		Brazil	1990	2007	Income
	China-Rural	1990	2005	Expenditure		Chile	1990	2006	Income
						Colombia	1995	2006	Income

Other Asian	Bangladesh	1992	2005	Expenditure	Costa Rica	1990	2007	Income <sup>a</sup>
	Cambodia	1994	2007	Expenditure <sup>a</sup>	Dominican Republic	1992	2006	Income <sup>a</sup>
	Lao PDR	2002	—	Expenditure	Ecuador	1994	2007	Income
	Malaysia	1992	2004	Income <sup>a</sup>	El Salvador	1995	2007	Income <sup>a</sup>
	Mongolia	2005	—	Expenditure	Guatemala	1998	2006	Income
	Pakistan	1991	2005	Expenditure	Honduras	1990	2006	Income
	Philippines	1991	2006	Expenditure	Mexico	1992	2008	Income <sup>a</sup>
	Thailand	1992	2004	Expenditure	Nicaragua	1993	2005	Income
	Vietnam	1998	2006	Expenditure	Panama	1991	2006	Income
					Paraguay	1990	2007	Income
					Peru	1990	2007	Income
					Trinidad and Tobago	1992	—	Income
					Uruguay-Urban	1992	2006	Income
					Venezuela, RB	1993	2006	Income

**Source:** PovcalNet, the online tool for poverty measurement developed by the Development Research Group of the World Bank (<http://econ.worldbank.org/povcalnet>).

**Note:** — = not available.

a. Poverty headcount \$2-a-day and private consumption expenditure from National Accounts available but not household mean income or expenditure.

the dataset with the per capita household expenditure PPP in 2005 constant terms. All rates of change are compound annual rates.<sup>30</sup>

To maintain consistency, we grouped countries according to the RICE classification and estimated the poverty-growth elasticities based on PCE instead of mean household income because climate change projections from RICE are available only for per capita consumption.

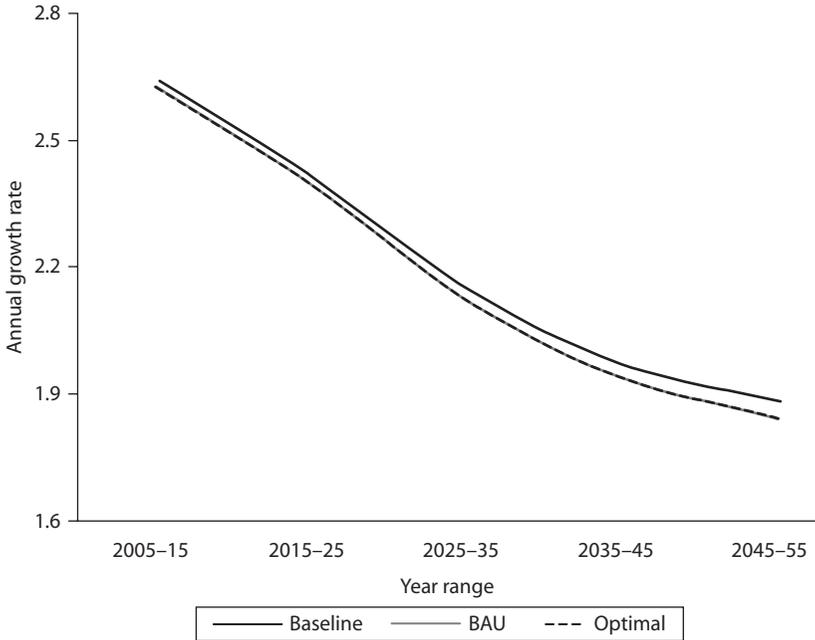
A second dataset includes per capita consumption projections for 10-year intervals from 2005 to 2055 based on the 2010 runs of the RICE model (Nordhaus 2010). From this model, we obtain growth rate trajectories for two scenarios under climate change: business as usual (BAU) and optimal abatement. The BAU scenario assumes that no climate-change policies are adopted. In contrast, under the optimal abatement scenario, those climate-change policies that maximize global economic welfare are adopted, with full participation by all nations starting in 2010. These two macro projections are the net of climate-change damages and abatement costs. To make these scenarios comparable, we create a baseline scenario (without climate change) based on the RICE 2010 model of Nordhaus (2010).<sup>31</sup> We modify the present investment as a function of the gross present output instead of the net present output of abatement and climate change.<sup>32</sup>

### ***Simulation Results***

Figure 2A.2 shows estimates of how climate change would affect global average PCE per capita according to RICE projections. Each of the three climate-change scenarios presents positive annual growth rates for the rest of the century, albeit with a decreasing trend. However, the growth gap widens between the baseline (no climate change) and the BAU or optimal scenarios.

Table 2A.2 presents estimations of poverty-growth elasticities for different countries and regions.<sup>33</sup> All coefficients are negative, meaning that a higher PCE per capita will translate into lower poverty rates. However, some regions respond faster to economic growth than others. For instance, with a 2 percent annual rate of growth and an initial headcount index of 40 percent in a relatively inelastic region such as Africa (with a poverty-growth elasticity of  $-0.45$ ), the headcount index will fall by less than 1 percent per year (or 0.35 percentage points in the first year). The headcount index will be halved in approximately 78 years. By contrast, in a relatively more elastic region such as Latin America with an elasticity of  $-1.35$  (triple Africa's elasticity), it will take about 26 years to halve the initial poverty rate.

**Figure 2A.2 Estimated PCE per Capita Growth under Three Climate-Change Scenarios**



*Source:* Authors' estimations based on Nordhaus 2010.

*Note:* The "baseline" scenario assumes a world without climate change. The "BAU" scenario assumes business as usual, following current climate-change trends. The "optimal" scenario assumes a world undergoing climate change but globally implementing strategies for optimal abatement of greenhouse gas emissions. PCE = personal consumption expenditure.

Tables 2A.3 and 2A.4 present poverty projections (measured as the number of people living below the \$2-a-day poverty line) under the BAU and optimal scenarios, respectively, compared with the baseline (no climate change) scenario for each region or country. In the absence of global warming, the world's headcount ratio would fall by more than 50 percent over the next 50 years, implying that 1.26 billion people would remain in poverty, most of them living in Africa and India. In absolute terms, climate change would result in 9.4–10.0 million more poor people globally by mid-century for the BAU and the optimal scenarios, respectively. The poverty impacts of climate change also show regional disparities, with India and Africa being the most affected.

Figure 2A.3 shows how many more people will be living in poverty between now and 2055 under the BAU and optimal scenarios relative to a world without global warming. Both curves slope upward through

**Table 2A.2 Poverty-Growth Elasticity, Selected Regions and Countries, 2010**

Region	Coefficient	Robust standard			95% confidence	
		error	t	p> t	interval	
European Union	-2.523	4.167	-0.610	0.606	-20.454	15.408
Eurasia	-1.863	0.286	-6.510	0	-2.473	-1.253
Middle East	-1.060	0.199	-5.320	0.118	-3.593	1.472
Africa	-0.446	0.170	-2.620	0.017	-0.803	-0.090
Latin America	-1.348	0.448	-3.010	0.008	-2.294	-0.403
Other Asian	-1.142	0.166	-6.880	0	-1.548	-0.736
<b>Country</b>						
Russian Federation	-2.078	n.a.	n.a.	n.a.	n.a.	n.a.
China	-1.112	0.620	-1.790	0.324	-8.987	6.763
India	-0.130	0.019	-6.890	0.092	-0.369	0.110

**Source:** Authors' estimations based on World Bank 2010b and data from PovcalNet, the online tool for poverty measurement developed by the Development Research Group of the World Bank (<http://econ.worldbank.org/povcalnet>).

**Note:** Results are weighted based on share of country population over total region population. Estimates were obtained using Ordinary Least Squares, regressing the annualized change in the FGT(0), or poverty headcount index, between household surveys on the time elapsed between the surveys and the annualized change in the personal consumption expenditure of national accounts (constant 2005 purchasing power parity). Standard errors corrected for heteroskedasticity and serial correlation. n.a. = not applicable.

**Table 2A.3 Potential Impact of Climate Change on Poverty under Baseline versus BAU Scenarios, Selected Regions and Countries, 2005–55**

*people living on less than \$2 a day (millions)*

Region	2005	2055		Difference
		Baseline	BAU	
European Union	24.36	0.87	0.93	0.06
Eurasia	26.98	0.24	0.25	0.01
Middle East	67.16	19.80	20.37	0.58
Africa	482.46	342.21	347.94	5.72
Latin America	95.08	7.49	7.67	0.18
Other Asian	70.58	23.78	24.33	0.55
<b>Country</b>				
Russian Federation	2.12	0.03	0.03	0
China	473.27	0	0	0
India	827.40	864.72	867.69	2.98
Total	2,069.40	1,259.13	1,269.21	10.08
Headcount rate	32.28	14.11	14.23	0.11

**Source:** Authors' estimations based on Nordhaus 2010.

**Note:** The "Baseline" scenario assumes a world without climate change. "BAU" designates a business-as-usual scenario, extending current climate-change trends.

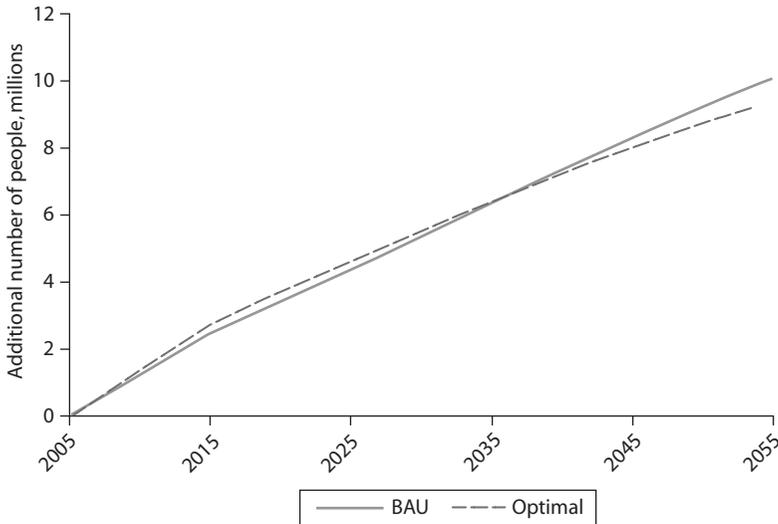
**Table 2A.4 Potential Impact of Climate Change on Poverty under Baseline without Climate Change versus Optimal Scenarios, Selected Regions and Countries, 2005–55**  
*people living on less than \$2 a day, millions*

Region	2005	2055		Difference
		Baseline	Optimal	
European Union	24.36	0.87	0.92	0.06
Eurasia	26.98	0.24	0.25	0.01
Middle East	67.16	19.80	20.36	0.57
Africa	482.46	342.21	347.45	5.24
Latin America	95.08	7.49	7.66	0.17
Other Asian	70.58	23.78	24.32	0.54
<b>Country</b>				
Russian Federation	2.12	0.03	0.03	0
China	473.27	0	0	0
India	827.40	864.72	867.53	2.82
Total	2,069.40	1,259.13	1,268.54	9.40
Headcount rate	32.28	14.11	14.22	0.11

Source: Authors’ estimations based on Nordhaus 2010.

Note: The “baseline” scenario assumes a world without climate change. The “optimal” scenario assumes a world undergoing climate change but globally implementing strategies for optimal abatement of GHG emissions.

**Figure 2A.3 Potential Impact of Climate Change on Global Poverty under BAU and Optimal Scenarios, 2005–55**



Source: Authors’ estimations based on Nordhaus 2010.

Note: “BAU” designates a business-as-usual scenario, projecting current climate-change trends. The “optimal” scenario assumes a world undergoing climate change but globally implementing strategies for optimal abatement of greenhouse gas emissions.

mid-century, implying that climate change will have a negative impact on poverty. In particular, under the BAU scenario, about 10 million more people will be living in poverty by 2055 than under the baseline (no climate change) scenario.

The optimal trajectory (based on climate-change policies that maximize intertemporal welfare) shows a higher incidence of poverty in the near future as more resources are diverted toward abatement efforts, hence reducing the per capita rate of economic growth. However, the initial negative impact of abatement on poverty is compensated in the future as the optimal policies reduce future warming.

## Notes

1. See annex 2A for a detailed description of the methodology and data used to project the impacts of climate change on poverty using the RICE (Regional Integrated Model of Climate and the Economy) model developed by Nordhaus (2010).
2. The within-country cross-sectional relationship is substantially weaker than the cross-country correlation, but it remains statistically significant and of an economically important magnitude, with a 1°C rise in temperature associated with a 1.2–1.9 percent decline in municipal per capita income (not GDP).
3. In Assunção and Chein Feres (2009), regional effects in Brazil are considered in the following five divisions: North, Northeast, Central-West, Southeast, and South.
4. For each municipality, they consider a sample comprising the nonmigrant households and those who outmigrate to other municipalities—but excluding migrants from other municipalities.
5. For a detailed description of IAMs in the context of climate change control, see Kelly and Kolstad (1999).
6. PAGE (Hope 2006) is an IAM used extensively by *The Stern Review* (Stern 2007).
7. It is a common practice to multiply the growth rate in GDP by 0.8 to approximate the growth rate in consumption. This adjustment factor, however, is not explicitly documented in any published paper that we are aware of.
8. *The Stern Review* reports Anderson's results based on the 95th percentile of the climate-change damage distribution. Under these higher damages, by 2100, climate change could increase the number of poor people by 46 million in South Asia and by 98 million in Sub-Saharan Africa.
9. It is useful to benchmark Nordhaus's (2010) BAU scenario against other IAMs. For example, PAGE 2002 estimates that the mean loss in world output in 2100

- would be 2.9 percent under its high-climate-change scenario. The RICE model presumes a somewhat larger 3.3 percent loss in 2105. Differences in inferences from various models depend more on whether one examines the mean impacts of uncertain climate change or the tails of the impact distribution.
10. Given the limitations in knowledge and large uncertainties surrounding climate change, its impact on economic growth, and the impacts of growth on poverty, this analysis (as well as Anderson's) should be viewed as indicative only of the *potential* consequences of climate change on global poverty. There are profound uncertainties at every stage in global warming modeling—uncertainties about future output growth; the pace and direction of technological change (particularly for low-carbon energy sources); migration patterns; climatic reaction to rising GHG concentrations; and the economic and ecological responses to changing climate and how impacts should be discounted.
  11. The RICE projections of annual per capita growth rates are decreasing over time. The annual world output growth also masks considerable regional disparities; for example, although China and India are expected to grow at a 3.6 annual per capita rate, the European Union will grow at a 1.8 annual rate.
  12. See Cline (2007) for a synthesis of impacts reported in the literature, and Hertel and Rosch (2010) for a review of methodologies.
  13. Autonomous adaptation is typically distinguished from planned adaptation, which refers to policy-based actions that are needed when market failures or other coordination problems hinder relevant collective responses to climate change.
  14. The authors consider seven types of households based on their primary sources of earnings (that is, where they earn 95 percent of their income): agricultural self-employed (farm income), nonagricultural (nonagricultural self-employed earnings), urban labor (urban households with wage labor income), rural labor (rural households with wage labor income), transfer payment-dependent, and two groups of households with nonspecialized income sources (urban diverse and rural diverse).
  15. The commonly used \$1-a-day standard, measured in 1985 international prices and adjusted to local currency using PPPs, was chosen for the World Bank's (1990) *World Development Report 1990: Poverty* because it was typical of the poverty lines in low-income countries at the time. International poverty lines were revised using the new data on PPPs compiled in the 2005 round of the International Comparison Program, along with data from an expanded set of household income and expenditure surveys. The new extreme poverty line is set at \$1.25 a day in 2005 PPP terms, which represents the mean of the poverty lines found in the poorest 15 percent of countries ranked by per capita consumption. The median poverty line for developing countries is \$2 a day in 2005 PPP terms. Poverty measures are prepared by the World Bank's Development Research Group. For details on data sources and methods used

in deriving the World Bank's latest estimates, see <http://iresearch.worldbank.org/povcalnet>.

16. Another feature of Hertel, Burke, and Lobell's (2010) model is that all households in each region face the same prices and have the same preferences. Therefore, the change in the estimated real cost of living at the poverty line is the same across strata for any given country.
17. Differences in the impact of cost-of-living changes on poverty for different types of households result from differences in poverty elasticities across strata within each country.
18. It should also be noted that the impacts of climate change are derived based on the current stock and distribution of endowments of land and labor.
19. The effect of climate change on the price of cereals in India is obtained from the ENVISAGE (Environmental Impact and Sustainability Applied General Equilibrium) model, a multisector computable general equilibrium model developed at the World Bank for assessing climate-change effects and policies. The model predicts that cereal prices will rise approximately 10 percent by 2040 because of warming.
20. Thus, in contrast to the seven types of households considered in Hertel, Burke, and Lobell (2010), in this model there is a continuum of households.
21. The estimates show that, in the absence of adaptation, a 1°C increase in annual temperature reduces gross productivity per hectare by 24–31 percent, which translates into a much smaller decline in consumption of 10.9–11.3 percent.
22. It is important to keep in mind that, in India, the mean level of aggregate household expenditure in the National Sample Survey accounts for only 60 percent of the PCE from the National Accounts (Ravallion 2003). Regarding the growth rate in mean consumption in India, it is a common practice to multiply the growth rate in GDP by 0.8 so as to get an approximation of the growth rate in consumption (see note 7).
23. There is a large literature on the extent to which short-term weather shocks in poor rural areas can have long-term effects on education, health, and nutrition, especially of children. For a recent review of these studies, see Baez and Mason (2008).
24. As previously discussed, the IPCC's SRES A2 scenario might not accurately represent the expected GDP and population growth rates and the consequential emissions path. As a result, the A2 scenario is an extreme one that overestimates the negative impact that climate change will have on poverty reduction efforts.
25. For further details, see Ferreira (2010).
26. This parameter could take any sign and magnitude depending on how the distribution changes with economic growth. In other words, the Lorenz curve is not constant over time (see Ravallion and Chen 1997).

27. These results are similar to those estimated by Ravallion (2001): a  $-2.50$  growth elasticity of poverty based on consumption versus a  $-1.96$  elasticity based on PCE per capita. However, caution must be taken in this comparison because these elasticities were computed for \$1 a day at 1993 PPP.
28. The PCE per capita has other measurement problems: Survey periods do not match exactly the periods used in national accounts. At the same time, changes in PCE can arise solely from the nonhousehold sector of the economy (Ravallion 2001, 2003; Ravallion and Chen 1997).
29. These data were obtained from PovcalNet, the online tool for poverty measurement developed by the Development Research Group of the World Bank (<http://econ.worldbank.org/povcalnet>).
30. Annualized differences in logs gave similar results (see Ravallion 1997).
31. Abatement costs are zero in the baseline scenario.
32. The RICE model assumes that saving rates remain constant.
33. The use of poverty-growth elasticities to estimate climate-change impacts has some appealing features, but it also has several limitations that must be taken into account when interpreting results. Even though other approaches, such as Bhalla (2002) and Hillebrand (2008), take into account distributional changes, we are assuming an unchanging within-country distribution of per capita income over time. In other words, we are not differentiating between growth and redistribution effects on poverty. We adopt this assumption mainly for two reasons: first, most empirical evidence found that the poor on average tend to share proportionately in the gains from economic growth, and this outweighed the impact of changes in the distribution (Datt and Ravallion 1992; Dollar and Kraay 2002; Kraay 2006; Ravallion 2001, 2007). Second, there is little scientific basis for predicting long-run distributional changes (Chen and Ravallion 2004). At the same time, we are assuming that the relationship between growth and poverty (the poverty-growth elasticity) for the next 50 years will remain constant. These two assumptions are indeed very restrictive, especially as we project poverty impacts for the distant future.

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## CHAPTER 3

# Too Little Too Late: Welfare Impacts of Rainfall Shocks in Rural Indonesia

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### Introduction

In Indonesia, annual rainfall patterns are critical to agricultural output and rural livelihoods. In the cultivation of rice, the country's most important crop, farmers typically grow seedlings in a small plot and then transplant them to flooded paddy fields when rainfall is sufficient. Thus, low cumulative rainfall at the beginning of the wet season can delay transplanting and subsequently harvesting (Heytens 1991). Such climate-induced delays in crop harvests can mean an extended hungry season for poor farmers with limited savings or stocks. Furthermore, these delays can also undermine the prospects for a decent second harvest later in the year.

Empirical studies have shown that in Indonesia the amount of rainfall from September to December—the early portion of the wet season—has a strong positive correlation with rice production output throughout the area planted and the area harvested in January to April. Between 1971 and 1998, the September–December rainfall explained more than 80 percent of the variation in both the planted and harvested rice areas in January–April (Naylor et al. 2001, 2002).

These same studies further linked rainfall to sea-surface temperature anomaly (SSTA) and to El Niño and La Niña climate patterns—supporting

proposed forecasting models to inform food policy planning. In extending climate production models down to the province level, Falcon et al. (2004) suggested that with improved forecasting models and timely dissemination, farmers could be notified of recommended cropping patterns to adapt to changing conditions, and agencies could be better positioned to mobilize relief efforts to assist poor and near-poor households affected by shocks.

Although extensive research has examined the rainfall-production links at the aggregate level, little is known about the welfare losses that households suffer from the rainfall shocks, irrespective of whether the shocks are induced by El Niño. Low-income households are believed to be the most vulnerable to the impacts of negative shocks, including rainfall shocks, for many reasons: their geographical locations, limited assets, limited access to resources and services, low human capital, and high dependence upon natural resources for income and consumption. Despite wide recognition of the threat of climate-induced shocks upon poor people, limited attention has been given to quantifying the effects of rainfall shocks at the household level. Our analysis considers the household welfare implications of both a late monsoon onset and low level of rainfall. As we note later, a certain amount of rainfall is needed in the 90-day post-onset period for rice to grow properly.

### ***Questions for Policy Makers***

With projections pointing to a greater probability of rainfall shocks in the future,<sup>1</sup> policy makers will need to know what policies can either mitigate the impacts or help households to cope. A good place to start is with the various social safety nets and other assistance programs already in place. Here we assess their role in helping households cope with the impacts of rainfall shocks or in mitigating those impacts. For instance, we consider the following:

- Programs that provide households with greater access to credit may help them cope with delayed or poor harvests.
- Grants that support public works projects may generate nonfarm employment opportunities in the community.
- Community block grants that are used to invest in more advanced irrigation infrastructure could help mitigate the impacts of the rainfall shocks.

Evidence from within Indonesia confirming or refuting such claims could help policy makers identify instruments to help protect vulnerable households. Using available data, we explore the potential moderating

effects of various programs. This chapter, therefore, analyzes the potential welfare impacts of rainfall shocks in rural Indonesia and draws relevant policy lessons.

### **Chapter Structure**

Following this introductory context, the chapter is organized as follows:

- “Methodology” examines the means of estimating how rainfall variability affects 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 (a) the degree of household- and community-level vulnerability, and (b) the moderating impact of existing assets and social protection institutions. Understanding these factors is critical to designing policies that will minimize exposure to these shocks and the impact of that exposure.
- “Weather and Survey Data” presents the household- and community-level data from the Indonesian Family Life Survey (IFLS) upon which the impact of rainfall shocks on poor rural households could be based. Weather station data from the study period is also discussed.
- “Empirical Results” lays out the findings reached from regression analyses, which quantified the impact of rainfall shocks on the studied households, and propensity score matching (PSM) to estimate the extent to which local social programs either mitigated the effects of the shocks or helped the households cope with them.
- “Conclusions and Policy Considerations” sums up the contributions of the study and how policy makers may use them to help identify and assess community-based interventions that may either mitigate the effects of climate change—in this case, the predicted low-rainfall shocks and their impact on food production—or help poor rural households to better cope with them.

### **Methodology**

Here we describe the methodology and analytical frameworks used to estimate the impacts of rainfall variability on household welfare in rural Indonesia and the potential moderating effects of community-based programs.

#### ***Vulnerability Defined***

First, the bedrock concept for studying the welfare impacts of weather shocks: the analytical framework must be consistent with the logic of

vulnerability. 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. Not surprisingly, these factors (endowments, behavior, social interaction) also determine the distribution of vulnerability.<sup>2</sup> The connection between individual and collective vulnerability deserves emphasis because it is impossible to consider individual achievement in isolation from the natural and social environment (Adger 1999).

An individual's or a household's vulnerability to livelihood stress depends on exposure to, and the ability to cope with and recover from, a given shock. Along these lines, some further definition is in order:

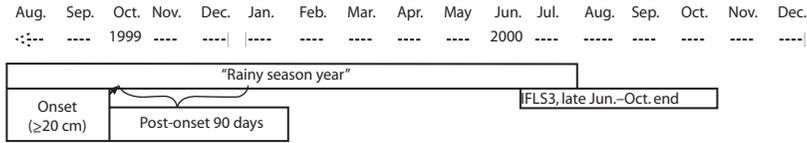
- *Exposure*, in this case, is a function of, among other things, climatic and topographical factors and the extent to which livelihoods depend on the weather.
- *The ability to cope* is largely determined by access to resources, the diversity of income sources, and social status within the community.<sup>3</sup>
- *Increased exposure* combined with a *reduced capacity to cope with, recover from, or adapt to* any exogenous stress on livelihood leads to *increased vulnerability*.

### **Shocks Measured**

Given the data limitations we face, we focus our strategy on exploiting cross-sectional variation in the data and linking our welfare indicator—real per capita expenditures or some component thereof (food versus nonfood expenditure)—to a rainfall shock. The shock is defined based on available rainfall data, focusing mainly on the locations of rural households. As noted earlier, the yield of crops such as rice and soybeans can be much affected by changes in precipitation patterns.

Given the importance of rice farming in Indonesia's rural economy, we define rainfall shocks in that context. A previous study of the delay in monsoon onset defined "onset" as the number of days after August 1 when cumulative rainfall reaches 20 centimeters (cm)—the amount of rain needed to moisten the ground enough for planting<sup>4</sup>—and "delay" as the number of days beyond the mean onset date over a 25-year period from 1979 to 2004 (Naylor et al. 2007). Because farmers typically begin planting after monsoon onset, a late onset may affect prospects for a second harvest later in the season and possibly change crop combinations, with potentially significant consequences for production and market prices.

**Figure 3.1** Timing of Typical Climate Events in Relation to the IFLS, 1999–2000



Source: Authors.

Note: IFLS3 = the third wave of the Indonesian Family Life Survey. IFLS1 was administered in 1993, and IFLS2 in 1997. cm = centimeter.

Delayed onset is an important determinant of harvest, but 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 three- to four-month grow-out period (Naylor et al. 2002). Thus, the second dimension of our shock involves the deviation of the amount of post-onset rainfall from the 25-year mean for each weather station. We define the amount of post-onset rainfall as the total amount of rainfall during the 90-day period following the monsoon onset date.

Figure 3.1 illustrates the timing of these weather events in relation to the 2000 Indonesian Family Life Survey (IFLS3) (RAND and CPPS 2000). Considering that the degree of rainfall variability can differ across areas and that households may adjust farming practices accordingly, we use standard deviations (SDs) from the intertemporal mean to help account for such spatial differences:

- *In terms of delay of monsoon onset*, we define a negative shock as being more than one SD above the 25-year mean.
- *In terms of the amount of post-onset rainfall*, we define a negative shock as being more than two SDs below the 25-year mean.

**Analytical Framework**

Given the interconnection between individual and collective vulnerability and adaptive capacity, our empirical analysis uses regression analysis to link an indicator of household welfare—that is, real per capita total expenditure or its food and nonfood components—to some rainfall shock while controlling for household characteristics and the province of residence. We estimate a regression equation of this form:

$$y_{ij} = \beta_0 + \beta_1 X_i + \beta_2 S_j + \beta_3 (S_j \times F_i), \tag{3.1}$$

where  $Y_{ij}$  represents per capita household expenditure of household  $i$  in community  $j$ ;  $X_i$  represents various control variables;  $S_j$  represents the

covariate rainfall shocks; and  $F_i$  is a binary variable representing rice-farming households.

Standard errors accounted for clustering at the community level and stratification by province and urban or rural sector in line with the complex survey design of the IFLS.

After analyzing the effects of rainfall shocks on welfare, we consider the potential moderating effect of various community-level programs. Ideally, we would like to measure, for the same household, per capita expenditures with and without the program of interest at a particular point in time. This is not possible, though, so we must seek alternatives. (If program placement had been done randomly, simply comparing average per capita household expenditure in communities with and without the program could have been a good option for evaluating whether a certain program helped households exposed to shocks.)

However, the placement of government programs is not likely to be random (Pitt, Rosenzweig, and Gibbons 1993). Many of the social safety net programs that emerged following the 1997 financial crisis were intended to protect the poor and thus targeted poorer communities and households, albeit with high leakage rates (Sumarto, Suryahadi, and Widyanti 2002). Given this potential for selection bias in program placement, the distribution of community and household characteristics is likely to differ between communities that have a program and those that do not have a program. One consequence of the endogeneity in program placement is that if the analysis does not address this issue, biased estimates of program effects are likely to result, especially when using cross-sectional data.

Recognizing that government assistance programs often target the poorest areas, we use PSM to investigate the role that various social programs in the community (such as safety nets and credit) could play in moderating the impact of the weather shock on household welfare, most likely by helping affected households cope with the shock. The PSM method comprises two main steps:

1. The propensity score model, which is used to predict the likelihood of a household or community receiving treatment—in this case, one of the social assistance programs. The predicted values are commonly called the propensity scores. Assuming that program placement is as good as random (conditional on observable community characteristics), we can consider two households with the same propensity score to be observationally equivalent.

2. Matching each household from the group *with* the program to equivalent households in the group *without* the program. Based on the propensity scores, the group constructed from matched households is comparable to the other. Hereafter, we will refer to the group of households in communities with a specific program as the “treatment group” and the constructed comparison group of households without the program as the “control group.” With the treatment and control groups defined, the average difference in the outcome variable can then be estimated.

We estimated propensity scores on covariates using probit regressions and retrieved their predicted values to allow for the matching of “treated” observations with those in the comparison group. For each program, a separate stepwise estimation of the probit specification was performed such that variables with a  $p$ -value less than .2 were added to the right-hand side. The dependent variable was a binary variable indicating whether a household resided in a community with the specific program of interest. The list of possible right-side variables for the stepwise estimation included household and community variables as well as binary variables for the different provinces.

The household variables always included in the model were household size, age of head, education level of head, household use of electricity, ownership of farmland, household nonfarm business, and household farm business. Candidate household variables were marital status of head and gender of head. The candidate community variables were 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; the shares of household heads with elementary, junior high, high school, and university education; and the share of households with an official letter verifying their status as poor. All rural households were part of the sample for the probit regressions.

After the propensity scores were estimated, observations in the treatment and control groups were trimmed to obtain a common support for the propensity scores. In terms of the matching procedure, we matched each treatment household to its “nearest neighbor” based on propensity scores. For each household in the treatment group, three households from the control group were matched with replacement based on the propensity score. To adjust for inexact matches of the propensity score, regression adjustments were performed as in Abadie et al. (2004). We then

compared average outcome for households in the treatment group (in communities with a specific program) with the average outcome for similar households in the control group (living in communities without the program under consideration).

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 let  $Y_i(0)$  denote the per capita expenditure outcome of household  $i$  in the absence of the attribute in the local community. Because both  $Y_i(1)$  and  $Y_i(0)$  are not observable, we must construct a counterfactual group of households in communities that do not have the “treatment” attribute of interest but have a similar probability of having the attribute based on observable community characteristics. Through a matching process, we define bias-corrected matching estimators,  $\hat{Y}_i(0)$ , in place of  $Y_i(0)$  (see Abadie and Imbens 2002; Abadie et al. 2004 for details) and estimate the sample average treatment effect for the subpopulation of the treated (SATT):

$$SATT = \frac{1}{n_1} \sum_{i|W_i=1} \{Y_i(1) - Y_i(0)\}, \quad (3.2)$$

where  $W_i = 1$  indicates that a household is in a community with the treatment attribute; and  $n_1$  is the sample size of the treated.

## **Weather and Survey Data**

We can study the impacts of extreme weather events on rural households by merging household- and community-level data from the IFLS3 with daily rainfall data covering a 25-year period. The combined data set contains information on rainfall, household expenditures, household-level socioeconomic characteristics, and community-level attributes.

### ***Household- and Community-Level Data***

The IFLS3 household and community surveys were fielded from late June to the end of October 2000. The community surveys include data on whether various social programs were presently conducted on a routine basis or recently conducted in 1999/2000 in the community. It should be noted that the data do not indicate which households actually participated in the programs.

The household-level data contain the consumption aggregate and its food and nonfood components. The food component consists of 37 food items (purchases and the value of own production or gifts) consumed

within the week before the survey. The nonfood component consists of frequently purchased goods and services (utilities, personal toiletries, household items, domestic services, recreation and entertainment, transport, sweepstakes, and so forth); less-frequent purchases and durables (such as clothing, furniture, medical, ceremonies, and taxes); housing; and educational expenditures for children living in the household. Transfers out of the household were excluded. All values were monthly figures and were in real terms. To obtain real values, both temporal and spatial deflators were used, using prices in December 2000 in Jakarta as the base.<sup>5</sup>

### ***Weather Data***

Using daily rainfall data from 1979 to 2004, we calculated the 25-year mean and SDs for monsoon onset and the amount of post-onset rainfall for 32 World Meteorological Organization (WMO) weather stations. The rainfall data from these weather stations were then matched to communities in the 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 covered a total of 267 communities and the 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. In rural areas, 3,290 households were matched to 27 stations; of those, 2,159 rural Java households were matched to 18 stations.

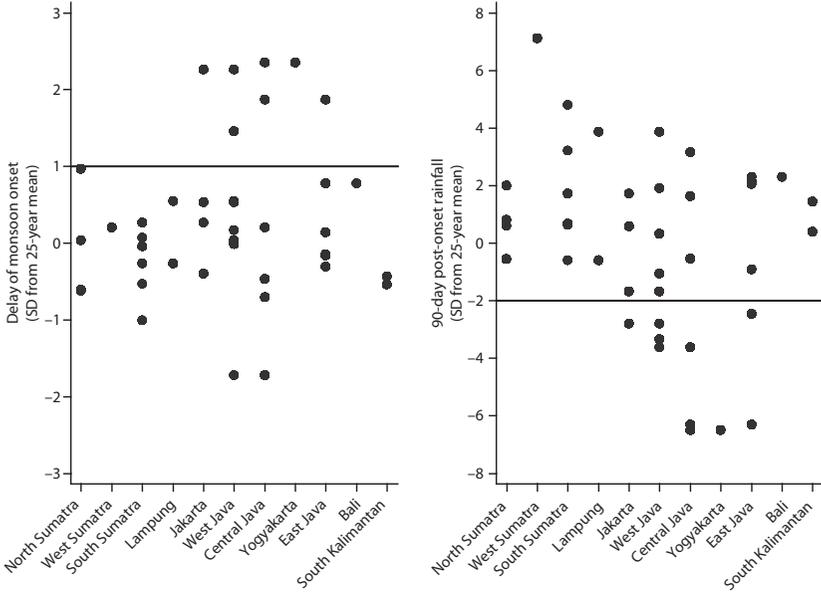
After merging available precipitation data and dropping observations with missing data, the sample size in the 2000 IFLS3 for our analysis shrank to 6,188 households from the initial total of 10,292. Data from additional weather stations would benefit this analysis by improving the level of disaggregation of weather data, but these data could not be obtained.

Figure 3.2 shows the variation by province in monsoon onset and post-onset rainfall in 1999/2000. With respect to delays in monsoon onset, only provinces in Java experienced a delay greater than one SD from the 25-year mean—thus experiencing a negative weather shock. As for the amount of rainfall during the 90-day post-onset period, again only provinces in Java experienced rainfall below two SDs from the 25-year mean—also constituting a negative shock.

### ***Summary Statistics***

The summary statistics of household expenditures, household characteristics, and rainfall shock exposure in rural Java are shown in table 3.1.

**Figure 3.2 Variation in Monsoon Onset and Post-Onset Rainfall in Indonesia, by Province, 1999/2000**



*Source:* Authors' estimates.  
*Note:* SD = standard deviation. The horizontal line on the left figure denotes 1 SD delay in the onset of the monsoon. The horizontal line on the right figure denotes a less than 2 SD in a 90-day post-onset rainfall.

Most of the household heads were married males without more than an elementary education. The vast majority of households used electricity. Half of the households owned farmland, and 44 percent were engaged in nonfarm 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. In our sample, 34 percent of the households were exposed to the “delay-of-onset” weather 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.

**Empirical Results**

Here we present our findings on (a) the impact of rainfall shocks on per capita household consumption levels and (b) the role that social programs may have played in helping households cope with the negative welfare impacts of rainfall shocks.

**Table 3.1 Summary Statistics for Households in Rural Java, 1999/2000 IFLS**

<i>Variables</i>	<i>Mean</i>	<i>Standard error</i>
Total PCE (rupiah per capita per month)	257,273	7,660
Food PCE (rupiah per capita per month)	154,389	4,332
Nonfood PCE (rupiah per capita per month)	102,885	4,745
Household size	4.06	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: junior 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 nonfarm 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

*Source:* Authors' estimates.

*Note:* HH = household,  $N = 2,159$ , IFLS = Indonesia Family Life Survey, PCE = per capita expenditure, SD = standard deviation.

For the first part (a), we used regression analysis to quantify the average reduction in household welfare levels among those exposed to low-rainfall shocks. For the second part (b), we used PSM to estimate the extent of the moderating effects offered by the various community-based programs.

### ***Welfare Impacts of Rainfall Shocks***

Given the importance of rainfed agriculture (particularly rice farming) to rural livelihoods in Indonesia, this study assessed the potential impact of rainfall shocks on per capita total household expenditure, including its food and nonfood components. Focusing on rural Java—the predominant rice production area in Indonesia—we used regression analysis to estimate the impacts on household expenditures.

Included in the regressions are 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; education level of head (binary variables for elementary, junior high, high school, and university); access to electricity; ownership of farmland; 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 and that has no access to electricity, no farmland, and no household farm or nonfarm businesses.

Using the two rainfall shock variables separately as well as together, we used three different specifications for our regressions:

1. The first includes a binary variable for delayed monsoon onset along with its interaction term with the binary variable for rice-farming household.
2. The second substitutes the post-onset low rainfall variable as the shock variable.
3. The third includes both rainfall shocks (late monsoon onset and post-onset low rainfall) along with their interaction terms. This third variation was used with different dependent variables, that is, per capita total household expenditure and its food and nonfood components.

As might have been expected, there is a strong positive correlation between household per capita expenditure and assets, namely education and ownership of farmland. All education coefficients are positive and significantly different from zero. For all five of the regressions reported in table 3.2, the magnitude of these coefficients increases 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 rather unusual. In general, the province of residence does not seem to matter in the explanation of variations in household welfare because the associated coefficients are not significantly different from zero. Having electricity certainly indicates wealth; this is manifested by a positive and significant effect on per capita expenditure. Similarly, owning farmland or a nonfarm business has a positive and significant impact on household expenditure and its components (food and nonfood).

**Table 3.2 Regression Results of Weather Shocks on Household Consumption in Rural Java, 1999/2000**

<i>Dependent variable (log)</i>	<i>Total PCE</i>			<i>Nonfood PCE</i>	<i>Food PCE</i>
	<i>Delay of onset shock</i>	<i>Post-onset low rainfall shock</i>	<i>Both shocks</i>	<i>Both shocks</i>	<i>Both shocks</i>
HH farm business—rice most valuable crop	0.002 (0.042)	0.056 (0.047)	0.041 (0.046)	0.072 (0.065)	0.034 (0.042)
HH farm business—other crop most valuable	−0.046 (0.044)	−0.047 (0.046)	−0.046 (0.045)	−0.117** (0.054)	0.003 (0.048)
Shock: delay of monsoon onset (>1 SD)	−0.042 (0.064)		−0.035 (0.065)	0.103 (0.084)	−0.132** (0.061)
Shock: post-onset low rainfall (<−2 SD)		−0.036 (0.054)	−0.027 (0.055)	−0.034 (0.076)	−0.019 (0.049)
HH farm rice × delay shock	0.024 (0.062)		0.072 (0.072)	0.037 (0.114)	0.118* (0.063)
HH farm rice × low rainfall shock		−0.120** (0.059)	−0.142** (0.067)	−0.256** (0.104)	−0.083 (0.057)
Household size	−0.145*** (0.008)	−0.145*** (0.009)	−0.145*** (0.008)	−0.136*** (0.011)	−0.148*** (0.008)
Age of head	0.015** (0.006)	0.015** (0.006)	0.015** (0.006)	0.017** (0.008)	0.016*** (0.006)
(Age of head) <sup>2</sup> (1/100)	−0.015*** (0.005)	−0.015*** (0.005)	−0.015*** (0.005)	−0.019** (0.007)	−0.015*** (0.005)
Married head	0.036 (0.077)	0.042 (0.076)	0.041 (0.077)	0.016 (0.086)	0.102 (0.078)
Female head	−0.019 (0.077)	−0.015 (0.076)	−0.016 (0.076)	0.007 (0.079)	0.012 (0.079)
Highest education of head: elementary	0.091** (0.044)	0.086** (0.042)	0.087** (0.042)	0.172*** (0.051)	0.039 (0.045)

*(continued next page)*

**Table 3.2** (continued)

<i>Dependent variable (log)</i>	<i>Total PCE</i>			<i>Nonfood PCE</i>	<i>Food PCE</i>
	<i>Delay of onset shock</i>	<i>Post-onset low rainfall shock</i>	<i>Both shocks</i>	<i>Both shocks</i>	<i>Both shocks</i>
Highest education of head: junior high school	0.214*** (0.071)	0.206*** (0.070)	0.207*** (0.070)	0.358*** (0.085)	0.123 (0.075)
Highest education of head: high school	0.506*** (0.084)	0.502*** (0.083)	0.503*** (0.083)	0.786*** (0.093)	0.300*** (0.087)
Highest education of head: university	0.212** (0.099)	0.205** (0.095)	0.205** (0.095)	0.350*** (0.117)	0.098 (0.088)
Central Java province	-0.072 (0.076)	-0.055 (0.073)	-0.057 (0.073)	-0.007 (0.097)	-0.075 (0.068)
Yogyakarta province	-0.038 (0.114)	0.004 (0.106)	0.005 (0.112)	0.044 (0.134)	-0.023 (0.115)
East Java province	-0.071 (0.058)	-0.063 (0.057)	-0.061 (0.056)	-0.016 (0.088)	-0.106** (0.047)
HH utilizes electricity	0.158** (0.066)	0.188*** (0.062)	0.188*** (0.062)	0.441*** (0.106)	0.060 (0.063)
HH owns farmland	0.114*** (0.032)	0.117*** (0.032)	0.116*** (0.032)	0.131*** (0.046)	0.080** (0.033)
HH nonfarm business	0.172*** (0.035)	0.170*** (0.034)	0.170*** (0.034)	0.228*** (0.044)	0.131*** (0.034)
Constant	11.972*** (0.199)	11.946*** (0.193)	11.952*** (0.191)	10.431*** (0.277)	11.574*** (0.170)
<i>N</i>	2,159	2,159	2,159	2,159	2,159
<i>R</i> <sup>2</sup>	0.196	0.200	0.201	0.189	0.175

*Source:* Authors' estimates.

*Note:* Standard errors are in parentheses. HH = household, PCE = per capita expenditure, SD = standard deviation.

\* $p < .10$  \*\* $p < .05$  \*\*\* $p < .01$

***Without weather shock.*** In the absence of a weather shock, our results show the following:

- 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.
- However, households running a farm business with nonrice crops as the most valuable had per capita nonfood expenditures about 12 percent lower than the reference household.

***With weather shock.*** Definition of the rainfall shock variable is important in our specifications.

***Delay in monsoon onset.*** When the weather shock is a delay in monsoon onset, our results show the following:

- Although the delay has a negative effect on the per capita *total* expenditures of rural households of Java, it is not statistically significant. (This is contrary to the finding reported in Korkeala, Newhouse, and Duarte [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.

***Post-onset low rainfall.*** When the weather shock is a decrease in rainfall during the 90-day post-onset period, our results show the following:

- If the amount of rainfall is below two SDs 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 *both total and nonfood per capita expenditures*.
- With exposure to the low rainfall shock, the *per capita total expenditure* of households engaged in rice farming is 12–14 percent lower than that of the reference household.
- With exposure to the low rainfall shock, the *per capita nonfood expenditure* is 26 percent lower, controlling for household attributes and province of residence.
- In contrast to those reductions in household total expenditure and nonfood expenditure, 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 latter result, frequently observed among rural households in various countries (Skoufias and Quisumbing 2005), suggests that rice farming households can protect their food consumption in the face of weather shocks. Thus, households manage to protect their food consumption at the expense of nonfood consumption. And, therefore, to the extent that reduced *nonfood* expenditures 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).

### ***Welfare Impacts of Social Programs***

As noted earlier, an individual's or a household's vulnerability 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 savings as well as the cash and in-kind transfers that are part of some social assistance programs.

We explored the role of the following six social assistance programs in mitigating potential negative welfare impacts of weather shocks in rural areas of Java:

- Access to credit through the Inpres (presidential instruction) Poor Villages Program
- Kampung Improvement Program, an informal housing-area upgrading program that provided basic services and infrastructure through community-based organizations
- Infrastructure Development Program, a community-based infrastructure development program (Sumarto, Suryahadi, and Widyanti 2002)
- Padat Karya (labor intensive) program, a loose collection of workfare programs sponsored by various government departments (Sumarto, Suryahadi, and Widyanti 2002)
- PDM-DKE (Regional Empowerment to Overcome the Impact of Economic Crisis) program, a block grant program for villages to support revolving funds for credit or public works projects that offer nonfarm employment opportunities (Sumarto, Suryahadi, and Widyanti 2002)
- Inpres Desa Tertinggal (IDT) (Program for Underdeveloped Villages), another block grant program targeting extremely poor villages (Sumarto, Suryahadi, and Widyanti 2002).

These programs may help households cope with the loss of farm income, smaller harvests, or higher prices by enhancing access to credit, providing cash or in-kind transfers, and expanding labor opportunities.

As discussed earlier, recognizing that government assistance programs often target poor areas, we used PSM to infer the moderating impact of some community-level interventions on the impact of the weather shock. For each of the community-based programs, we estimated the average treatment effect of the intervention on per capita household expenditure components among households exposed to the shock and in communities with the program of interest (that is, SATT).

To assess whether the potential program benefits differ according to the presence or absence of a shock, we also estimated the SATT among households not exposed to the shock. In addition, we repeated the procedures using another variation of the PSM specification and limited the subsample to rural households engaged in a farm business.

The results in table 3.3 are shown as the percentage difference in mean per capita expenditures between the treatment and control groups. The panel on the left side of table 3.3 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 subsample of households exposed to the shock that were engaged in a farm business.<sup>6</sup>

***Inpres and IDT program results.*** The results for the Inpres Poor Villages Program and the IDT Program indicate positive and significant average treatment effects that are greater among rural households engaged in farm businesses than among all rural households.

*Inpres.* Among households exposed to a low-rainfall shock, those in communities with the Inpres credit program had per capita expenditure averaging 15.7 percent higher than that of the control group (without Inpres).

Among households in communities not exposed to the shock, the Inpres program did not show any significant difference in average treatment effects.

For the subsample engaged in farm businesses and hit by a low-rainfall shock, average per capita expenditure levels in communities *with* the program were 24.9 percent greater than in communities *without* the program. Among households not exposed to the shock, the average treatment effect was -13.4 percent and statistically significant at the 95.0 percent confidence level.

These results suggest that the greater access to credit furnished by the Inpres program may have allowed households to borrow to maintain

**Table 3.3 Moderating Effects of Community-Based Programs for Rural Java Households Exposed to Post-Onset Low Rainfall Shocks: Average Treatment Effects Based on PSM***percentage difference between treatment and control groups*

<i>Low rainfall shock</i>		<i>All rural households</i>		<i>Rural households engaged in farm business</i>	
		<i>Yes</i>	<i>No</i>	<i>Yes</i>	<i>No</i>
Inpres Poor Villages Program (credit)	ATT	15.7**	-5.9	24.9**	-13.4***
	n1	245	604	136	398
	n0	299	1,305	165	857
IDT Program (block grants)	ATT	16.0**	-2.2	23.3**	5.3
	n1	231	198	145	161
	n0	489	323	299	197
Kampung Improvement Program (community based)	ATT	24.8***	16.6**	19.3*	12.2
	n1	287	280	167	205
	n0	406	527	289	336
Infrastructure Development Program (community based)	ATT	4.9	21.4*	-10.9	5.3
	n1	168	61	78	56
	n0	447	32	279	23
Padat Karya program (public works)	ATT	13.3*	10.9	-3.7	-10.4
	n1	167	168	64	71
	n0	499	518	308	210
PDM-DKE program (block grants)	ATT	0.4	-8.1	15.0	5.4
	n1	137	485	55	216
	n0	565	1,199	371	758

*Source:* Authors' estimates.

*Note:* ATT = average treatment effect on the treated, expressed as the percentage difference in average per capita total household expenditure between treatment and control groups, IDT = Inpres Desa Tertinggal (Program for Underdeveloped Villages), Inpres = presidential instruction, n1 = number of households in treatment group after trimming, n0 = number of households in control group after trimming, PDM-DKE = Regional Empowerment to Overcome the Impact of Economic Crisis.

\* $p < .1$  \*\* $p < .05$  \*\*\* $p < .01$ 

household consumption in locations where rainfall shocks might have diminished harvests—constituting an important coping mechanism for households affected by the shocks.

*IDT.* Similarly, the average treatment effects of the IDT—which provided block grants for underdeveloped villages—were 16.0 percent and 23.3 percent among all rural households exposed to the shock and among the subsample engaged in farm businesses, respectively. Both of these results were significant at the 95 percent confidence level. However, the corresponding treatment effects among households *not* exposed to the shock were smaller (-2.2 percent and 5.3 percent, respectively) but not statistically significant.

These results suggest that the IDT block grant program may have provided some relief to rural households hit by the rainfall shock, in particular to farming households, likely by generating local employment opportunities through public works projects.

***Kampung Improvement Program results.*** The results for the Kampung Improvement Program indicate positive average treatment effects of 24.8 percent and 16.6 percent for the sample of rural households (treatment group and control group, respectively), and 19.3 percent and 12.2 percent, respectively, for the subsample of households engaged in farm businesses.

In contrast to the effects of Inpres and IDT, the ATT (average treatment effect) is smaller for the subsample engaged in farm businesses, although the 19.3 percent result is only weakly significant at the 90.0 percent confidence level. The ATT for the subsamples not exposed to shock was smaller than the corresponding results for the subsample with shock.

The exact mechanisms by which this program might have yielded these results are not apparent, but one might guess that infrastructure improvements help to mitigate the impacts of low-rainfall shocks. Given the positive results, further investigation would be worthwhile.

***Padat Karya program results.*** The Padat Karya safety-net program had an ATT of 13.3 percent among rural households exposed to the low-rainfall shock, an only weakly significant result at the 90.0 percent confidence level. The other results for the Padat Karya program were statistically insignificant. However, this labor-intensive workfare program exhibits potential as an effective safety net in alleviating the stress that may have been induced by a low-rainfall shock.

***Infrastructure and PDM-DKE program results.*** The results for the Infrastructure Development Program and PDM-DKE (public works or credit access) safety-net program were statistically insignificant. It is not possible to say much about the effectiveness of these programs in the context of rainfall shocks.

***Summary of Social Welfare Program effects.*** Overall, the results suggest that access to credit and public works projects in communities can help households *cope* with weather shocks and thereby play a strong protective role during times of crisis. For their part, community infrastructure

improvement programs may *mitigate* the impacts of the shocks. In light of these findings, these policy instruments should receive due consideration in the design and implementation of climate-change adaptation strategies.

## Conclusions and Policy Considerations

Scant empirical evidence exists on the welfare losses that households experience as a consequence of weather shocks. In principle, low-income households 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.

On a broader scale, despite wide recognition of the threat that climate-induced shocks pose for the poor, researchers and policy makers have given only limited attention to either quantifying the effects of weather extremes or identifying targeted measures that could mitigate the poverty impacts or at least help the poor to cope with them.

It is to those ends that this study seeks to contribute.

Above, we have analyzed the potential welfare impacts of rainfall shocks in rural Indonesia with a focus on households engaged in family farm businesses, particularly rice farming because rice is a staple food in Indonesia. We also attempted to identify community interventions capable of dampening the adverse impact of climate change and extremes.

Our basic approach was to exploit cross-sectional variation in the data and, focusing mainly on rural households, link a welfare indicator (real consumption per capita) or some component thereof (food versus nonfood expenditure) to a weather shock defined based on available rainfall data.

We considered two types of shocks: (a) delayed monsoon onset and (b) rain shortfall in the 90-day period following monsoon onset. We found that delay in the monsoon onset does not have a significant impact on the welfare of rural households. However, the low-rainfall shock after monsoon onset negatively affects rice farm households. Nonfood expenditure per capita is the most affected component among rice farm households, suggesting that those households protect their food expenditure in the face of weather shocks. Further study is needed to better understand these choices and their implications for climate-change adaptation strategies.

To identify potential policy instruments that might moderate the welfare impact of weather shocks, we used PSM to evaluate several social

assistance programs. Our results indicate that credit availability, the existence of safety nets, and public works programs offer the strongest cushion for these types of shocks. This is an important consideration for the design and implementation of strategies to protect poor, vulnerable households.

Indeed, individuals' 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.

## Notes

1. Adapting projections by the Intergovernmental Panel on Climate Change to local conditions, Naylor et al. (2007) predict that by 2050, the probability of a 30-day delay in monsoon will increase from 9–18 percent currently to 30–40 percent. This delay, combined with increased temperature, could reduce rice and soybean yields in Indonesia by as much as 10 percent.
2. 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).
3. 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.
4. It is believed that about 100 cm of rain are needed throughout the season for cultivation.
5. 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.
6. We also attempted to extend this analysis to only those farmers who indicated rice as their most valuable crop, but the data thinned out and precluded application of this approach to this subsample.

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## CHAPTER 4

# Timing Is Everything: How Weather Shocks Affect Household Welfare in Rural Mexico

Emmanuel Skoufias and Katja Vinha

### Introduction

Despite uncertainty over the exact magnitudes of the global changes in temperature and precipitation, climatologists and policy makers alike widely accept that climate variability will likely deviate significantly from its historical patterns (IPCC 2007).<sup>1</sup> Considering that millions of poor households in rural areas all over the world depend on agriculture, there are increasing concerns that the change in climatic variability patterns will make rural households in developing countries even more vulnerable than they already are, thus seriously challenging development efforts globally. In view of this imminent threat to poor people, it is critical to have a deeper understanding of the effectiveness of household adaptation strategies as well as targeted measures that could mitigate the poverty impacts of erratic weather.

With these considerations in mind, this chapter presents an analysis of how climatic variability affects household welfare in the rural areas of Mexico. We use the first two waves of the nationally representative Mexican Family Life Survey (MxFLS), carried out in 2002 and 2005/07, to examine whether increases or decreases of rainfall and growing degree

days (GDD)—a cumulative temperature measure—by more than one standard deviation from their respective long-run means, significantly affect rural households' ability to smooth expenditures.<sup>2</sup>

### ***Traditional Risk Management Strategies***

Erratic weather may affect agricultural productivity, which (depending on how effective a household's risk management strategies are) may translate into lower income.<sup>3</sup> Based on historical experience and the multiplicity of economic and institutional constraints they face, rural households in Mexico, as most rural households all over the world, have developed traditional strategies for managing climatic risk. For instance, households may undertake before-the-fact income-smoothing strategies and adopt low-return, low-risk crop and asset portfolios (Rosenzweig and Binswanger 1993).

In Mexico specifically, smallholder farmers have adapted to climatic risk in Tlaxcala (Eakin 2000). For example, farmers plant both fast-maturing but low-yield corn as well as slow-maturing but high-yield varieties, or they may switch from the more-profitable corn to wheat depending on the prevailing weather. They may also change fertilizer and pesticide use depending on the climate and diversify geographically by having plots of land in different locations. Furthermore, to get through difficult times, households have used their savings (Paxson 1992); taken loans from the formal financial sector (Udry 1994); sold assets (Deaton 1992); or sent their children to work instead of school to supplement income (Jacoby and Skoufias 1997). More strategies include the management of income risk through after-the-fact adjustments in labor supply such as multiple job holding and engaging in other informal economic activities (Kochar 1999; Morduch 1995).

All of these actions have traditionally enabled households to spread the effects of income shocks from unanticipated negative events through time. However, certain individual characteristics, such as lower educational attainment, may increase the vulnerability of households to risk (Skoufias 2007).

### ***Combining Household, Agricultural, and Meteorological Data***

To the extent that the current, traditional risk-coping mechanisms are not effective in protecting welfare from erratic weather patterns, the increasingly erratic patterns associated with climate change will certainly reduce the effectiveness of these coping mechanisms even further—thus increasing household vulnerability as well.

However, quantitative evidence is quite scarce on how successful the traditional risk management strategies are in protecting household welfare from weather shocks in Mexico. Other studies, relying on the perceptions of respondents about the incidence of different types of shocks—such as floods, droughts, freezes, fires, and hurricanes—include Skoufias (2007) and De la Fuente (2010). None of these earlier studies, however, used actual meteorological data.

***Household expenditures.*** To better understand who is most affected by weather shocks and where such effects are more pronounced, we first quantify the effect of weather shocks on households nationally and subsequently for different climatic regions based on average precipitation. By separating the sample along climate criteria, we group together households that face similar challenges from similar shocks.

Because food expenditures are sometimes protected better than non-food expenditures (see Skoufias and Quisumbing 2005; chapter 3 of this volume), we analyze the impacts of weather on per capita expenditures on food and nonfood items separately. Furthermore, it is quite possible that households' resilience and ability to adapt to changing weather and environmental conditions differs significantly depending on access to different risk-coping mechanisms. Therefore, we investigate the extent to which some such mechanisms—namely, assets, land titling, education, and access to transportation infrastructure—change the ability of households to smooth their consumption.

***Agricultural cycles.*** One distinguishing feature of our study is that we investigate the extent to which the timing of the climatic shock matters within the agricultural cycle. We match each household to the weather shocks experienced in the following:

- The prior agricultural cycle (encompassing an October–March dry season and an April–September wet season)
- The prior wet season
- The first three months of the wet season preceding the household survey (the MxFLS), which would be April, May, and June—the *pre-canícula* period (*canícula* being a mid-summer drought period in Mexico)—that are critical months for many corn growers (Eakin 2000).

***Weather shocks.*** In addition, although rainfall-based measures have widely been used in determining the effect of weather shocks on

consumption,<sup>4</sup> temperature-based measures have not received the same attention. Temperature measures have been used to assess the economic impacts of climate change through crop yields (Deschênes and Greenstone 2007; Schlenker and Roberts 2008), but they have not been included in models of weather-shock impact on consumption. To capture this other important aspect of weather, we include weather shocks based on the cumulative temperature during the three time periods considered.

### ***Chapter Structure***

Although this chapter is limited to a general discussion of the study's methods and findings, readers can find the full presentation of algorithms, data tables, and detailed analysis in the authors' previously published paper (Skoufias and Vinha 2012). From here, the chapter is organized as follows:

- "Mexico's Climate and Agriculture" presents background and context for the data and analysis, explaining how the growing cycles and weather affect agricultural productivity and crop choices.
- "Household, Climate, and Agricultural Data Sources" lays out (a) the data used from the MxFLS and authors' surveys; (b) how climate data were measured; (c) how weather shocks were defined; (d) how weather was measured throughout the growing cycle; and (e) how household groups were identified for analysis and matched to weather data by municipality.
- "Empirical Analysis" examines the impact of the measured weather shocks on both household consumption per capita and households' ability to protect their consumption from weather shocks, depending on the location, the timing, and the nature of the shock.
- "Conclusions" sums up the primary findings and recommends more region-specific analyses and more finely tuned climate categories to better estimate the effects of households' risk management strategies and their potential implications for public policy.

### **Mexico's Climate and Agriculture**

Both rainfall and temperature are important factors affecting crop yields. Extremes of either rainfall (drought or flood) or temperature (extremely cold or extremely hot) will negatively affect yields and thus, potentially, household income and consumption as well. Even within normal ranges

of rainfall and temperature, *additional* rainfall or *warmer* days may increase yields in one climate but reduce yields in another.

### ***Effects of Temperature and Precipitation***

In Mexico, depending on the state, temperatures lead to either higher or lower yields (Galindo 2009), suggesting heterogeneous effects from weather shocks. For example, corn production benefits from higher temperature in Hidalgo, Estado de México, Puebla, and Querétaro and decreases with higher temperature in Baja California de Sur, Campeche, Chiapas, and Guerrero. Similarly, the optimal levels of rainfall (below and above which yields fall) depend on the class of crops (Galindo 2009).

Projecting a future scenario, a long-run climatic change with a temperature increase of 2°C and a rainfall decrease of 20 percent would increase the amount of unsuitable land for corn production by 8 percent in a sample of seven corn-producing municipalities from Estado de México, Puebla, Veracruz, and Jalisco (Conde et al. 1997). Likewise, a 2°C increase in temperature but a 20 percent *increase* in rainfall would increase the amount of land unsuitable for corn production by 18 percent. In another simulation, when raising the temperature by 4°C above the mean and coupling that alternatively with a 20 percent *increase* and a 20 percent *decrease* in rainfall, the amount of land unsuitable for production increased by 20 percent and 37 percent, respectively.

Based on historical production patterns, droughts are responsible for more than 90 percent of all crop losses in Mexico (Appendini and Liverman 1994).

### ***The Growing Cycle***

The agricultural year in Mexico runs from October to September. The dry season runs from October to the end of March, and the wet season from April to the end of September. About 82 percent of cultivated land is rainfed (INEGI 2007) and thus highly susceptible to weather fluctuations. In the wet season, corn is produced in 59 percent of the cultivated land devoted to seasonal crops; in the dry season, corn is produced in 31 percent of seasonal cropland. The total area cultivated is more than six times greater in the wet season than in the dry season (INEGI 2007).

More important, many small-scale farmers use corn 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 shorter growth cycles but are not as useful for household consumption, is considered a last resort (Eakin 2000).

The growing cycle for corn can be divided into three phases<sup>5</sup>:

- *The vegetative phase* lasts 40 to 60 days. The longer it takes for the seed to germinate (that is, 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, frost can significantly damage the plant.
- *The reproductive phase* begins with ear formation for about 20 days and continues with the grain fill stage, which takes an additional 20 to 30 days. Inadequate water availability during this phase greatly affects yields, with the impacts being the greatest during the ear-forming stage. Also, extremely warm temperatures (above 32°C) during the second half of the vegetative phase and the reproductive phase reduce yields.
- *The maturation phase*, the final growing phase before harvest, lasts 20 to 35 days.

Planting later in the season ensures that the seed germinates quicker, but 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, the *canícula* (included in figure 4.1) affects farmers’ planting decisions. In general, farmers want the corn to flower (for the ear formation stage to be complete) before the onset of the *canícula* to better the odds of crop survival in case the *canícula* is drier than normal (Eakin 2000). Therefore, the months leading up to the *canícula* are of special importance in Mexico.

**Figure 4.1 Timing of Agricultural Cycle in Mexico Relative to the MxFLS, 2001–02**

2001									2002					
Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	Apr.	May	Jun.
Wet season 2001						Dry season 2002						Wet season 2002		
Pre-canícula			Canícula											
Weather shocks for MxFLS 1 households (wet season 2001 and dry season 2002)												MxFLS 1 households surveyed		

*Source:* Authors.  
*Note:* The *canícula* is a mid-summer drought period in Mexico. MxFLS 1 = the first wave of the Mexican Family Life Survey. The second wave of the survey was performed between 2005 and 2007.

## Household, Climate, and Agricultural Data Sources

### *Household Data: The MxFLS*

For the household data, we used the first two waves of surveys from the Mexico Family Life Survey (Rubalcava and Teruel 2006). The first wave of the survey interviewed 3,353 rural households in 75 different localities in all regions of the country and was conducted between March 2002 and August 2002, with most of the information collected in April, May, and June (as shown in figure 4.1).<sup>6</sup> The second wave of the survey was collected between 2005 and 2007, with most of the data collected from May 2005 to September 2005. The follow-up survey interviewed 3,271 households.

Both waves collected detailed information on each household member, including basic characteristics, educational attainment, and migration. Furthermore, the survey collected detailed information on household expenditures.<sup>7</sup> Separate surveys were administered to the leaders of each locality about infrastructure and programs accessible in the locality.<sup>8</sup>

### *Climate and Weather Data*

The climate data for this paper came from the Mexican Water Technology Institute (Instituto Mexicano de Tecnología del Agua, or IMTA). The IMTA has compiled daily weather data from more than 5,000 meteorological stations scattered throughout the country. The data span a long period—from as far back as the 1920s to the present (up to 2007 for this analysis)—and contain information on precipitation and maximum and minimum temperature. The meteorological stations registered these variables daily, and we used this information to interpolate daily values of these variables for a geographic centroid in each municipality in Mexico.<sup>9</sup> A locality-based centroid was determined as the simple average of the latitudinal and longitudinal coordinates of all the localities listed in the National Institute of Statistics and Geography's (Instituto Nacional de Estadística y Geografía, or INEGI) 2005 catalogue corresponding to each municipality.

We chose this method over a population-weighted average because that alternative would have biased the interpolation toward urban rather than rural areas. The interpolation method, from Shepard (1968), is a commonly used method that accounts for relative distance and direction between the meteorological stations and the centroids. (For a more detailed description, see Skoufias and Vinha 2012.)

We carried out an independent interpolation for every day between 1950 and 2007, for each municipality. Because not all meteorological

stations existed throughout the entire period and because they sometimes failed to report their records, each interpolation was 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 in the earlier years, which had a corresponding effect on our interpolations. Thus, interpolations for the year 1950 are less reliable than those for 2007.

### ***Agricultural Data: Rainfall and GDD***

From these 1951–2007 weather data, we calculated the total rainfall and GDD for the following:

- Each agricultural year (October to September)
- Each wet season (April to September)
- Each pre-canícula period (April, May, June)—the months leading to the canícula.<sup>10</sup>

Instead of maximum or minimum temperatures, we used GDD: a cumulative measure of temperature based on the minimum and maximum daily temperatures. GDD measures each day's contribution 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. For example, some corn varieties require 2,450 GDD, whereas others require 3,000 GDD to mature; some wheat varieties require only 1,800 GDD, whereas others require 2,000 GDD.<sup>11</sup>

Each crop also has specific base and ceiling temperatures that 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 (and, in fact, temperatures above the ceiling may be detrimental to growth).<sup>12</sup> In short, 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.<sup>13</sup> To determine the cumulative GDD at any point for a specific cultivation, the daily GDD since planting are summed.

Given the mixture of different crops grown in the survey areas, we used the generalized bounds of 8°C and 32°C (for example, as in Schlenker and Roberts 2008). In our specific case, any daily minimum or maximum temperature below 8°C is treated as being 8°C, and any daily minimum or maximum temperature above 32°C is treated as being 32°C. Thus,

a day with a minimum and maximum temperature of 8°C or below will yield no GDD, whereas a day with a maximum and a minimum temperature of 32°C or above will yield 24 GDD.

### **Measuring Weather Shocks**

For our measures of weather shocks, we first construct 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 as well as their standard deviations. This date range balances (a) the need to calculate the historic means with as many years of information as possible with (b) the need to exclude recent years that changing climate may have affected. Furthermore, we use a 35-year span for the baseline because there is incomplete information for some months for some of the municipalities.<sup>14</sup> In our sample of rural municipalities, the average climate is based on 15 to 35 years of information. Among the rural households in the sample, 75 percent live in localities within municipalities that have at least 30 years of complete weather information from 1951 to 1985.

Our chosen measures of weather shocks are based on the degree of deviation from the 1951–85 average weather. A shock is identified by those observations where the weather variable is more than one standard deviation away from its long-run mean. By this definition, a municipality experienced a *negative* rainfall shock if the prior period's rainfall was at least one standard deviation *less* than the average 1951–85 rainfall. A municipality experienced a *positive* rainfall shock if the prior period's rainfall was at least one standard deviation *more* than the average 1951–85 rainfall.

Thus, a total of four measures describe shocks in the prior year's (or wet season's or pre-canícula period's) weather: negative and positive temperature (GDD) shocks and negative and positive rainfall shocks.

We also use two aggregate shock measures—one for rainfall and the other for GDD—such that the indicator is equal to one if the municipality experienced either a positive or negative shock. A rainfall shock of one standard deviation translates to an average of about 30 percent higher or lower rainfall. One standard deviation of GDD is, on average, about 8 percent from the mean.

During the 1986–2002 period, there were more *temperature* shocks (both negative and positive) than *rainfall* shocks, suggesting that temperature was a more variable aspect of weather than rainfall compared with pre-1986 weather (Skoufias and Vinha 2012).

### ***Matching Household and Weather Data***

The survey date is used to match each household to the weather information. Each household is assigned the wet season and dry season before the survey date. That is, if a household was surveyed in the dry season of the agricultural year  $t$ , the weather shocks would be 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 are based on the weather in dry season  $t$  and wet season  $t-1$ .

To illustrate, for the households in the 2002 wave of the MxFLS, the weather variables of interest are rainfall and GDD based on April 2001 to March 2002 weather (as shown previously in figure 4.1). Thus, we are assuming that the households' income and production would be based on the harvests of the 2001 wet season and the 2002 dry season—and not on the harvest from the 2002 wet season, which is roughly contemporaneous to the survey. Given the long time span for data collection in the second wave of MxFLS, not all households are matched to weather shocks from the same two seasons (as is the case in first wave), but households are matched with the previous completed dry and wet seasons before being surveyed. The longer survey period implies that there are more than 75 possible distinct weather pairs in the original 2002 MxFLS sample of municipalities.

Although the number of municipalities from which the household surveys are drawn is relatively small, we do still have some variability in the weather variables. There are municipalities that experienced positive and negative rainfall as well as GDD events, and there were more GDD shocks than rainfall shocks in the sample, which is in line with the national trend from pooling all shocks from 1986 to 2002.<sup>15</sup>

The original MxFLS municipalities 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 of them at least 75 percent of the land is rainfed and thus with production highly susceptible to weather conditions.<sup>16</sup> Also, in most of them, corn is cultivated on at least 50 percent of the land that is cultivated with seasonal crops in the wet season. In all states, the cultivated area in the wet season is greater than the area cultivated in the dry season. These interpolated weather figures (Skoufias and Vinha 2012) suggest that—for an average rural household in our sample—we can expect 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-canicula period is of interest.

## Empirical Analysis

To estimate the degree of consumption smoothing, we adapt a commonly used equation (for example, Cochrane 1991; Mace 1991; Townsend 1994). Instead of using income, we use weather shocks as proxies for it (as detailed in Skoufias and Vinha 2012).

We employ both aggregate and disaggregate shocks. For the disaggregated shocks, we differentiate between negative and positive shocks because the effects of weather shocks on income may differ depending on the direction of the shock. Specifically, a locality has a negative or positive weather shock, respectively, when the weather variable (rainfall or GDD) in a given period is at least one standard deviation less than, or more than, the long-run average climate in the locality.

### *Measures of Household Consumption*

We use two distinct measures of consumption—food and nonfood—because weather shocks may have different effects on different types of consumption (see Skoufias and Quisumbing 2005; chapter 3 of this volume). The per capita expenditures on all nonhealth- and nonfood-related items are based on the household's reported spending

- *In the week prior to the survey* on tobacco and public transportation
- *In the prior month* on personal items, cleaning products, general services, recreation, gambling, and communications
- *In the prior three months* on clothing, toys and baby items, household items, health care, and vehicle maintenance
- *In the prior year* on appliances, furniture, house repairs, vehicles, vacation and taxes
- *In the current school period* on education.

Following Thomas et al. (2010), we subtract annual health spending from the total expenditures (which average about 11 percent of total expenditures) because most health spending follows illness and thus is not welfare-improving.

Second, we use the logarithm of per capita annual expenditures on food. The average share of food expenditures in our sample is 41 percent of total expenditures (without considering health expenditures). Included in food expenditures are the estimated value of goods consumed from own production and the value of goods received as gifts in the week before the survey.<sup>17</sup> The expenditure measure we use reflects expenditures after

including the monetary value of self-production or resources from 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 implications on the future long-run poverty status of the household is not explored in this book.

Higher observed expenditure may be a consequence of higher local prices faced by households rather than a greater quantity of goods consumed. To account for covariate price effects, all expenditures are adjusted by monthly price variation at the regional level.<sup>18</sup>

### ***Measures of Other Household Characteristics***

Besides the weather shock variables, we include variables that 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)
- The household's asset index<sup>19</sup>
- 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).

The household composition and asset index variables enter as changes between the two MxFLS waves of surveys. The rest of the independent variables reflect the household's situation in the second survey period. Furthermore, to account for the potentially different amount of resources available or any seasonal consumption patterns (depending on the season in which the household responded to the expenditure survey), we introduce a season indicator variable.<sup>20</sup> To ensure that the weather shocks reflect the experience of the household, only those households where the head did not migrate in the two years before each of the surveys are included.

Furthermore, we exclude from our analyses households that report extremely large (greater than 16 standard deviations from the sample mean) per capita food expenditures or per capita nonhealth or nonfood expenditures. This excludes five households from the study. On average, the households reported slightly lower per capita food expenditures in

the second round than in the first round. The expenditures excluding health and food are higher in the second round than in the first, but the average is influenced by a few households with large expenses. In the second round, there are fewer children per household and more adults per household (as expected, given that the same set of households is interviewed three or four years after the first survey). In 2005, more than half of the household heads had not completed primary school, and there are fewer household heads without primary education in the arid municipalities than in the humid ones. About one-fifth of the households were headed by a female. About one-third of the households did not have access to a sewage system or a toilet in their dwelling unit.

For the full descriptive statistics of the variables used in these analyses, see Skoufias and Vinha (2012).

### ***Expenditures and Weather Shocks***

We use two different samples: (a) those households that did not experience any type of weather shock in 2002 and (b) all households. By limiting our households to those that did not experience a shock in 2002, we simplify the weather shock variables.

We then differentiate the shocks by their direction—that is, negative or positive shocks—to determine whether the direction of the shock matters. Furthermore, we assign each household to a climate region based on the average annual rainfall to determine how households in different climates are affected by different types of shocks.

The full analysis (Skoufias and Vinha 2012) suggests that an average household's annual consumption is protected against any negative income shocks from unusual weather. If the shocks do have a negative impact on agricultural production (and income), the results suggest that households are either able to protect themselves after the fact by changing their agricultural practices in response to the weather shocks or, in the case of reduced agricultural revenue, households can 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 by accessing credit.

When we exclude households that experienced a weather shock in 2002, none of the aggregate shock coefficient estimates is statistically significant. After including them, we observe 22 percent higher non-health and nonfood expenditures after annual rainfall shocks and 18 percent higher expenditures on food after wet-season rainfall shocks.

The results suggest that the shocks augment income. Such increases are possible if the climatic conditions brought about by the shocks improve the growing conditions for the crops cultivated.

By expanding the set of shocks analyzed into negative and positive shocks, we observe that the aggregate shocks mask some of the variation in the effects of shocks. In the sample where households with a shock in 2002 are excluded, there are large effects from positive GDD shocks in the wet season and pre-canícula period. However, these effects disappear once the excluded households are included in the analyses, suggesting that such effects are particular to some subset of households. Once households that experienced a weather shock in 2002 are included, annual negative rainfall shocks and annual positive GDD shocks are associated with 45 percent greater nonhealth and nonfood expenditures and 36 percent greater food expenditures, respectively.

That is, after either a drier-than-normal or a warmer-than-normal prior agricultural year, households spend more—suggesting that if the shocks increase productivity, at least some of the transitory income is spent.

To check the robustness of our results, we exclude from the sample municipalities in which the average distance of the closest 20 weather stations exceeds 20 kilometers. The farther away the stations, the greater the potential for measurement error.

The average results above do not, however, capture any variability across different regions. Mexico spans many different climatic regions, and certain shocks that increase yields in one climate may decrease yields in another climate. Using INEGI (2009) climate classifications, we classify each municipality as either a low- or high-precipitation municipality. Low-precipitation municipalities are those classified as very dry, dry, or semidry. High-precipitation municipalities are those that are classified as subhumid or humid.<sup>21</sup> In all, there are 27 low-precipitation municipalities and 48 high-precipitation ones.<sup>22</sup>

In contrast with the average results, grouping households by the average precipitation of their municipality suggests that not all household can smooth their consumption from weather shocks.

***Dry-climate households.*** Households in municipalities with a dry climate have lower consumption after three types of weather shocks:

- Nonfood and nonhealth expenditures are lower after a negative GDD shock in the pre-canícula period.

- Food expenditures are lower after a negative rainfall shock in the pre-canícula period and after a negative annual GDD shock.
- Households have higher per capita expenditures after a negative annual GDD shock (on nonhealth and nonfood expenditures) and after a positive annual GDD shock (on food).

The results from a negative annual GDD shock for the low-precipitation municipalities are contradictory: On one hand, food consumption decreases, suggesting that income decreases and consumption is not fully protected. On the other, nonhealth and nonfood expenditures actually increase, suggesting increases in income.

Together, the results suggest that there is a change in the spending *composition* after a cooler-than-normal year in the more-arid municipalities. In the arid regions, households are not protected from shocks experienced during the pre-canícula period; drier or colder periods affect the annual food and nonfood and nonhealth expenditures.

***Humid-climate households.*** Households in subhumid and humid climates are better able to protect their annual expenditures. Only negative wet-season GDD shocks are associated with a decrease in nonfood and nonhealth expenditures; however, the effect is no longer statistically significant when we exclude municipalities farther than 20 kilometers from the average weather station.

In contrast with the results for the low-precipitation municipalities, shocks during the prior pre-canícula period do not have a statistically significant impact on expenditures. Both negative and positive annual rainfall shocks lead to higher nonfood and nonhealth expenditures. Also, negative wet-season rainfall shocks lead to higher expenditures on both food expenditures and nonfood and nonhealth expenditures, suggesting that less-than-average rain raises income.

### ***Differences in Household Expenditures by Observable Characteristic***

To determine whether the impact of a weather shock differs for different types of households, the estimate is made separately for different subpopulations. Ideally, we would analyze the subpopulations by climatic region, but the limited number of distinct municipalities (and sets of weather shocks experienced) do not allow for such detailed analyses. Instead, we use all the rural households in the sample and use food expenditures as the measure of consumption.

These analyses reveal only the average national effect and not any differing effects of shocks in the various climatic regions. However, as was the case above with the average effects for different regions, any negative coefficient estimates at the national level suggest that some portion of the population may not be fully protected. The populations of interest are

- Low- or high-asset households
- Households with less- or more-educated heads
- Households without or with a land title
- Households living in a locality without or with a bus station.

To ensure that we are capturing effects for a particular subpopulation, we include only those households that did not change status between the two surveys.<sup>23</sup>

***Effects of household characteristics on risk management after shocks.***

One after-the-fact risk management strategy is selling assets to smooth consumption (Deaton 1992). Households with a greater number of assets may be in a better position to do so. Therefore, households are divided into two asset groups: (a) those that in the first round had fewer than five assets and (b) those that had six or more assets. The median number of assets is five.

In our sample of rural households, we find that asset scarcity is not associated with inability to smooth consumption. We do not find inability to smooth consumption even with lower cutoff values for the asset-poor subpopulation.

Focusing on specific assets—whether the household owns title to land—again we do not observe those without a title being less able to smooth consumption. Households with less-educated heads may be more prone to the effects from negative income shocks (Skoufias 2007), but as with asset poorness, we do not find that to be the case on average in rural Mexico.

***Effects of accessibility of locality on risk management after shocks.***

The last characteristic potentially affecting risk-sharing mechanisms that we explore is the locality's accessibility. Greater integration of the locality into the regional economy and access to opportunities outside of the community gives households more opportunities to manage risks. To this end, we separate the sample by those households in communities without a bus stop and those in communities with a bus stop. Communities

with a bus stop have at least some public transportation to other localities and most likely also have better infrastructure and integration in general.

The results from the analysis show that, for our sample of municipalities,

- *Households in communities without a bus stop* cannot smooth consumption after any type of a GDD shock during the wet season or after a positive GDD shock in the pre-canícula period; and
- *Households in municipalities with a bus stop* cannot smooth their consumption after a negative GDD shock during the wet season or after a positive rainfall shock in the pre-canícula period.

However, the results must be interpreted with caution because only 37 municipalities reported information and did not change their status between the two rounds of the survey. Furthermore, because the presence of a bus station is not exogenous to the characteristics of the community, the coefficient estimates may be capturing effects of other covariant characteristics.

## Conclusions

We have examined the impacts of weather shocks (defined as rainfall or GDD of more than one standard deviation from their respective long-run means) on household expenditures per capita. Our results suggest that households cannot always protect their consumption from weather shocks and that some weather shocks increase expenditures, potentially because of a transitory increase in income when shocks improve growing conditions.

The effects of weather shocks on household expenditures vary according to the timing of the shock and the climatic region. Contrary to other research (see chapter 3 of this volume; Skoufias and Quisumbing 2005)—at least among rural Mexico households—we do not find evidence that food expenditures are more protected than nonfood expenditures.

Although the average rural household in our sample can smooth consumption such that no weather shock reduces expenditures, when the households are grouped by the average precipitation of their municipality, we observe that some households *cannot* smooth consumption. Households in arid climates are especially prone to lower expenditures after weather shocks. In arid regions, colder- or drier-than-average weather during the pre-canícula period negatively affects household consumption.

Nor do we find conclusive evidence on the effects of access to various risk management strategies in aiding an average household in the sample to smooth consumption. Given the heterogeneity in household responses to different climate shocks, ideally the analyses should be carried out separately for each climatic region.

Further research—using more finely tuned climate categories and a greater number of distinct municipality-year pairs—would shed light on the robustness of the results. More municipalities would also lead to better estimates on the effects of various before- and after-the-fact risk management strategies that may be available at the municipal level.

## Notes

1. The Intergovernmental Panel on Climate Change's (IPCC) 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 ranging from months to thousands of years. The World Meteorological Organization (WMO) defines the norm as 30 years. "Climate" differs from "weather," which refers to atmospheric conditions in a given place at a specific time. The term "climate change" indicates 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).
2. Weather may affect the well-being of individuals through other channels as well. For example, climate changes may increase (or decrease) the prevalence of certain diseases and thus affect health outcomes. Chapter 5 of this volume explores the impacts of weather shocks on children's health as measured by their height-for-age in rural Mexico.
3. In general, households can better insure their consumption against idiosyncratic shocks—shocks that affect only a particular household, such as the death of a household member—than they can 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).
4. See, for example, chapter 3 of this volume as well as Dercon and Krishnan (2000); Jacoby and Skoufias (1998); Paxson (1992); and Rosenzweig and Binswanger (1993).
5. The description of corn's growth cycle is adapted from Neild and Newman (1990).
6. Rural households are considered to be those in localities with less than 2,500 inhabitants.
7. MxFLS collects information on the value spent purchasing various categories of goods—food; dining out; health care; transportation; personal items; education; recreation; cleaning services; communications; toys, baby articles, and 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. It is not possible to estimate the value of goods consumed from own production because this value and the value of goods received from others are reported jointly.

8. There are several localities in each municipality. In MxFLS 1, only two municipalities had more than one locality sampled.
9. We use the National Institute of Statistics and Geography's (INEGI) 2005 geographic definitions, covering 2,451 municipalities.
10. Given that the agricultural year runs from October to September, the first agricultural year that we used is 1951, and therefore we used only the last three months of the 1950 calendar year.
11. For other important crops in Mexico, the required GDD are 2,400 for beans and 2,200 to 2,370 for sorghum. The GDD values are taken from IANR (n.d.).
12. For details of the calculation, see Skoufias and Vinha (2012).
13. We used the modified GDD formula, where the minimum and maximum temperatures are adjusted before taking the average. See, for example, Fraisse, Bellow, and Brown (2010).
14. A particular month is coded as missing if none of the 20 closest weather stations reported data for five or more consecutive days.
15. For the data set, see Skoufias and Vinha (2012).
16. For the table displaying these data, see Skoufias and Vinha (2012).
17. Because of the way in which the expenditure survey was administered, we cannot separate the value of “consumption from own production” from the value of goods received as gifts. About 7 percent of the rural households obtain more than 50 percent of their food from nonpurchased sources. On average, however, rural households obtain about 7 percent of their food from nonpurchased sources.
18. For this calculation, see Skoufias and Vinha (2012).
19. The asset index is the sum of whether the household owns land, a residence, another house, a bicycle, a 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.
20. For example, Paxson (1992) finds seasonal consumption patterns.
21. The average minimum and maximum annual precipitations are 200 millimeters (mm) and 600 mm, respectively, for the arid regions and 900 mm and 1,400 mm, respectively, for the humid regions.
22. For the full results for households in low-precipitation and high-precipitation municipalities, see Skoufias and Vinha (2012).
23. For the detailed survey results, see Skoufias and Vinha (2012).

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## CHAPTER 5

# Growing Precious Resources: Climate Variability and Child Height in Rural Mexico

Emmanuel Skoufias and Katja Vinha

### Introduction

Climate-induced erratic weather patterns can mean the difference between abundance and poverty, health and disease—and, to the rural Mexican children surveyed for this study, early growth or stuntedness that can affect the rest of their lives.

In Mexico, rainfall and temperature patterns greatly affect the growth cycle of crops and thus also household consumption, especially in rural areas. To the extent that climate change is an imminent reality, as climate scientists widely accept (IPCC 2007), millions of agriculture-dependent households worldwide may find themselves even more vulnerable to tenuous livelihoods that have increasing unpredictability.<sup>1</sup> Furthermore, a changing climate will likely affect the prevalence of diseases, adding to potential welfare losses.

### Erratic Weather and Health

The health consequences from climatic variability may depend, among other things, on both the timing of weather shocks—for example, deviations from long-term averages of temperature and precipitation—and on

key individual and household characteristics. For example, weather shocks during a time of relative food scarcity may affect child health more adversely than similar shocks during times of relative food abundance. Malnourished children are also more likely to become ill (Scrimshaw 2003)—an issue we investigate by examining the extent to which the timing of the climatic shock within the agricultural cycle matters for health.

Research must start addressing the needs and policy options of a world in which such shocks may become even more pronounced, if not permanent, given the paucity of quantitative data on how successful traditional strategies will be to protect household health and welfare in the face of weather shocks such as drought and flood. This analysis seeks to increase our understanding of both (a) the magnitude of climate-change consequences and (b) targeted policy measures or public programs that could either mitigate any harmful health effects of erratic weather or help people adapt to them.

To that end, this chapter analyzes the health impact of climatic variability on children 12–47 months of age in the rural areas of Mexico, using the 1999 Encuesta Nacional de Nutrición (ENN, National Nutrition Survey) and meteorological data from the Instituto Mexicano de Tecnología del Agua (IMTA, Mexican Institute of Water Technology). In particular, we quantify the extent to which unusual weather negatively affects height-for-age.

### **Traditional Agricultural Adaptation**

As chapter 4 of this volume discusses in greater detail, rural households in Mexico have traditionally turned to several strategies to prevent or offset large income losses during occasional lean years, when suboptimal climatic and other growing conditions have reduced their harvests. For example, smallholder farmers have adapted to climatic risk in the Tlaxcala region of Mexico by planting different crop varieties,<sup>2</sup> adjusting fertilizer and pesticide use to various climatic conditions, and diversifying geographically by having plots of land in different locations (Eakin 2000).

However, to the extent that climate change leads to more volatile weather, the lean years may become more frequent, potentially exhausting traditional ways of coping. As a result, households become less able to protect their own welfare and become more vulnerable. As erratic weather affects agricultural productivity—depending on how effective households' risk management strategies are—food becomes

less available, and thus both incomes and overall household consumption may decrease.<sup>3</sup>

### **Focus on Early Childhood Health, Growth**

On top of that scenario, temperature and precipitation anomalies may increase the prevalence of vector-borne, waterborne, and water-washed diseases and determine heat- or cold-stress exposure (Confalonieri et al. 2007). Many parasitic and infectious species survive and reproduce under highly specific environmental conditions, and a slight change in precipitation or temperature could render previously uninhabitable areas suitable for some of these species. Specifically in Mexico, several studies have shown positive correlations between temperature and vector- and food-borne illnesses (SEMARNAT 2007).

The study discussed here focuses on how weather affects the health outcomes of children younger than 48 months who live in rural areas. Early childhood health not only affects children's current well-being but may also determine their cognitive development as well as their quality of life and productivity as adults (see, for example, Doyle et al. 2009).

Children grow faster between the ages of zero and three than at any other time, and thus delayed growth may affect overall growth (Martorell 1999).<sup>4</sup> In developing countries, although children are born, on average, at the mean of standardized height-for-age, there is a sharp decline in their average height-for-age from ages zero to 24 months and no subsequent catching up in the first five years of life (Shrimpton et al. 2001). However, there is some evidence that, under the right conditions, children whose growth was stunted may be able to catch up later in life (see Adair 1999 for findings on Filipino children; Godoy et al. 2010 for findings on Bolivian children).<sup>5</sup> Furthermore, some evidence indicates that weight gain during the first two years of life had a large effect on schooling outcomes, whereas weight gain between two years and four years of age had a weaker one (Martorell et al. 2010).

The existing literature on weather, disease, growth, and child welfare also includes these findings:

- Weather-caused nutritional shocks during the first years of life have lasting effects on productivity, even if the household can overcome poverty later (Alderman 2010).
- Height-for-age and weight-for-age are strong predictors of school achievement, and therefore stunted growth between 12 months and

36 months of age is associated with poorer cognitive development (Victora et al. 2008).

- Malnutrition from insufficient food intake or as a byproduct of repeated diarrheal infections can structurally damage the brain and impair motor development in infants, which in turn affects cognitive development (Guerrant et al. 2008; Victora et al. 2008).
- A correlation between infectious diseases and IQ is based on the competition between energy needs for the development of the brain and energy needs to fight off disease (Eppig, Fincher, and Thornhill 2010). The authors single out diarrheal diseases as potentially the most energy consuming.

Overall, childhood health also has been found to affect adult health as well as the following:

- *Employment* (Case, Fertig, and Paxson 2005)
- *Cognitive abilities* (Case and Paxson 2008; Grantham-McGregor et al. 2007; Maluccio et al. 2009)
- *Educational outcomes* (Alderman, Hoddinott, and Kinsey 2006; Glewwe and Miguel 2008; Maluccio et al. 2009)
- *Productivity* (Hoddinott et al. 2008).

Such findings underline the importance of focusing on the health outcomes for young children.

### **Height-for-Age as a Proxy for Health**

Because the agricultural cycle in Mexico consists of a dry season from October to March and a wet season from April to September, we distinguish among four types of precipitation and temperature shocks: precipitation and temperature shocks in the agricultural year and wet season before the health assessment ( $t-1$ ), and precipitation and temperature shocks in the agricultural year and wet season two agricultural years ( $t-2$ ) before the health assessment ( $t$ ).

Resilience and adaptability to changes in weather and environmental conditions may also differ significantly across the population spectrum by socioeconomic characteristic. For example, Rose (1999) finds that rainfall shocks affect girls and boys differently. Behrman and Hoddinott (2005) find that, in Mexico, children are taller who participate in the Programa de Educación, Salud y Alimentación (PROGRESA, the Education,

Health, and Nutrition Program—called “Oportunidades” since 2002), which is an antipoverty program with a nutritional component. If so, participation in such programs might also protect children in the event of unusual weather. A mother’s education may also play a role, interacting with weather shocks such that erratic weather affects children of less-educated mothers differently from children of more-educated mothers. For instance, among Mexican children, a positive correlation is found between a mother’s education and cognitive abilities and her child’s height-for-age score (Rubalcava and Teruel 2004).

To better ascertain the effect of the climatic variability on child health, we use height-for-age as a proxy for health and interact the weather shocks with individual characteristics such as gender, educational attainment of the mother, or participation in supplemental nutrition programs. To examine geographically heterogeneous effects, we separate the sample by region and altitude.

## Overview of Findings

We find some evidence that both unusual rainfall and unusual temperature affect children’s height-for-age and thus potentially their short- and long-term health and productivity. We cannot determine whether the effects derive from changes in agricultural income (thus consumption) or from changes in the prevalence of communicable diseases and ailments associated with different weather conditions, but the results suggest that potentially both pathways are important.

More specifically, the following general findings emerged from the study, pertaining to four types of weather shocks:

- *After a positive rainfall shock* (greater-than-usual precipitation), children were shorter than the average, regardless of region or altitude.
- *After a negative rainfall shock* (less-than-usual precipitation), children were taller than the average (to a statistically significant extent in the Central region and at high altitudes) in the Pacific and Gulf and Caribbean regions.
- *After a negative temperature shock* (cooler-than-usual temperatures), children were shorter than the average in the Central and South regions of the country as well as at higher altitudes.
- *After a positive temperature shock* (warmer-than-usual temperatures), no statistically significant impacts were found on average, but certain subpopulations in some regions are affected depending on when the shock

occurred. A positive shock occurring in 1999 would lead to shorter-than-average boys and children between 12 and 23 months, while children of less-educated mothers would be shorter than average if there was a temperature shock in 1998.

## Chapter Structure

The rest of the chapter is organized as follows:

- “Past Research: The Weather-Consumption-Health Nexus” reviews some of the literature on the impact of weather on consumption and on the prevalence of disease, both of which affect health.
- “Context and Methodology” presents background concerning the timing of weather shocks in Mexico with respect to the late-1999 ENN; lays out how the climate and socioeconomic data were measured; and describes the data sources used.
- “Results: How Weather Shocks Affect Rural Children’s Height” presents the authors’ analysis of the impact of weather shocks on height-for-age among rural Mexican children.
- “Discussion and Conclusions” summarizes the findings and presents the authors’ conclusions and recommendations.

## Past Research: The Weather-Consumption-Health Nexus

One could think of the environment, health, and consumption as parts of one simple system (as shown in figure 5.1), in which health and consumption are two important dimensions of welfare: Consumption, measured at the household level, is influenced by the environment. Health, measured at the individual level, is influenced by both the environment and consumption.<sup>6</sup> To see the interaction among the three facets, it is instructive to think of each impact in isolation from the other two.

### *The Environment and Consumption*

The environment affects consumption in rural areas mainly through its effect on current agricultural production or income because crop yields are a function of precipitation and temperature. Depending on the household’s ability to cope with income fluctuations, a decrease in income brought on by bad weather may translate into reduced consumption (Dercon and Krishnan 2000; Jacoby and Skoufias 1998). In addition, the



(c) the impact of any changes the household and individual can make in their consumption to either mitigate the effects of, or adapt to, a given weather shock.

Studies on the consequences of weather shocks for individual welfare generally use some specific health outcome as the preferred measure. The evidence from other countries suggests that both gender and age matter. For example, consider the following findings:

- In rural India, a positive rainfall shock increases the survival probabilities of girls more than that of boys (Rose 1999).
- Drought has a small but transient effect on the body mass index (BMI) of women but not of men (Hoddinott 2006).
- A drought experienced at 12 to 24 months of age affected children's annual growth rate—an impact that persisted for the four years of the study (Hoddinott and Kinsey 2001). No such effect was found for weather shocks experienced later in life.
- In rural Indonesia, women who had lived their first year of life in a place where the rainfall exceeded the area's average rainfall are taller as adults, have completed more years of education, and live in wealthier households (Maccini and Yang 2009). The authors did not find any such impacts either on men's outcomes or from weather shocks experienced later in life.

In addition, a particular environmental shock may have not only a direct negative impact on health but also a positive one indirectly through consumption. For example, in Mexico, 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 benefits agricultural production depends on the crop, region, and season in which the weather change occurs. In Mexico, higher temperatures increase corn production in some regions but decrease it in others (Galindo 2009). Similarly, the optimal levels of rainfall (below and above which yields fall) depend on the class of crops (Galindo 2009).

In general, within a normal range of precipitation and temperature, more rainfall or warmer days should increase yields in temperate climates but will likely reduce yields in tropical climates. However, extremes of both rainfall (drought or flood) and temperature (extremely cold or extremely hot) reduce yields and thus potentially income and consumption as well. Therefore, the impacts on humans can differ pending on the underlying average climatic conditions. Malnutrition and other negative

health outcomes are possible if food consumption is reduced as a result of a weather event, especially if before the event the household or individual was barely consuming the required nutritional needs.

### ***Complex Interactions***

The impact of weather changes on health get even more complex.<sup>7</sup> The prevalence and range of a particular pathogen, disease vector, or animal reservoir are determined by specific ranges of temperature, precipitation, and humidity (Patz et al. 2003). Whether an unusually rainy or dry period increases disease prevalence depends on the region's specific climate. 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, 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 (influenced by temperature), malaria, and dengue (influenced by rainfall and humidity).

In general, extreme temperatures are lethal to disease vectors. An increase in precipitation will generally improve breeding conditions. However, extremely high precipitation (floods) may, on one hand, reduce infectious diseases by eliminating breeding grounds and, on the other, cause other vectors such as rodents to come into more frequent contact with humans. Extremely low precipitation (droughts) may create stagnant pools of water from streams and rivers, which are good breeding grounds for vectors, thus increasing the prevalence of the diseases associated with such vectors. In addition, besides vector-borne pathogens, water- and food-borne pathogens (causing enteric infections) are also susceptible to precipitation and temperature. 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.

## **Context and Methodology**

### ***Background***

Mexico has a substantial population living in poverty. In 2005, the Consejo Nacional de Evaluación de la Política de Desarrollo Social (CONEVAL, National Council for the Evaluation of Social Development Policy) estimated that 47 percent of the national population lived in poverty, with

18 percent of the population in extreme poverty (CONEVAL 2005). For all of Mexico, in 2006, 15.5 percent of zero- to five-year-olds had *height*-for-age Z-scores of less than  $-2$  standard deviations (stunted), and 3.4 percent of zero- to five-year-olds had *weight*-for-age Z-scores of less than  $-2$  (WHO n.d.). In rural areas, the rates were slightly higher, with the height-for-age and weight-for-age Z-scores below  $-2$  for 24.1 percent and 4.9 percent, respectively, among the zero- to five-year-olds (WHO n.d.).<sup>8</sup>

Furthermore, about 82 percent of cultivated land in Mexico is rainfed (INEGI 2007) and thus susceptible to weather fluctuations. The dependence on rainfed agriculture varies by region, with the Pacific and Gulf and Caribbean regions relying most heavily on it (96 percent and 97 percent, respectively). However, even in the North, 68 percent of the cultivated agricultural land is rainfed. Together, these statistics suggest that a relatively large population of the country could be at risk from weather fluctuations.

The agricultural year in Mexico runs from October to September, comprising a dry season from October to the end of March and a wet season from April to the end of September. For all regions (except for the Gulf and Caribbean region), more than 50 percent of cultivated land during the wet season is in seasonal crops. Corn is of special importance, with more than 25 percent of cultivated land devoted to its production during the wet season, and many small-scale farmers use corn 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 shorter growth cycles but are not as useful for household consumption, is considered a last resort (Eakin 2000).

In this context, and given the increasingly erratic weather patterns widely attributed to climate change, we examine the impacts of weather shocks on the stature of children between 12 and 47 months of age in Mexico. Weather shocks are defined as either rainfall or growing degree days (GDD, a cumulative measure of temperature) that are more than one standard deviation from their respective long-run means.

### **Data Sources**

**Household and health data.** The empirical analyses use data for the last quarter of 1999 (early in the 2000 agricultural year) from the following:

- The ENN collected by the Instituto Nacional de Estadística y Geografía (INEGI, National Institute of Statistics, Geography and Informatics); and
- The Secretaría de Salud de México (Secretariat of Health).<sup>9</sup>

Table 5.1 depicts the timing of the health survey relative to the range of dates used to determine the previous years' weather shocks. The survey interviewed 7,180 rural households in 174 municipalities, collecting general information on all household members and more detailed information (including anthropometric measures and illnesses in the prior two weeks) for females between 12 and 49 years of age and for all children 12 years or younger.<sup>10</sup>

**Climate data and weather shock measurements.** The climate data come from the IMTA. For a detailed discussion of the IMTA's compilation of daily weather data, see chapter 4 of this volume, for which similar weather data were gathered.

**Calculating rainfall and temperature data.** From these weather data, we calculate the total rainfall and cumulative GDD for each agricultural year (October to September) and for each wet season (April to September).<sup>11</sup> Instead of using maximum or minimum temperatures, we use GDD—a cumulative measure of temperature based on the minimum and maximum daily temperatures. GDD measures the temperature degree contribution of each day to the maturation of a 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 GDD to mature, whereas different wheat varieties only require between 1,800 and 2,000 GDD.<sup>12</sup> Furthermore, each crop has specific base

**Table 5.1 Agricultural Cycles in Mexico Relative to the ENN, 1997–2000**

Agricultural years														
1997			1998				1999							
Oct.	...	Mar.	Apr.	...	Sep.	Oct.	...	Mar.	Apr.	...	Sep.	Oct.	Nov.	Dec.
Dry season 1998			Wet season 1998			Dry season 1999			Wet season 1999			Dry season 2000		
Weather shocks ( $t-2$ )					Weather shocks ( $t-1$ )									
										ENN survey conducted ( $t$ )				
Age at dry season of agr. year ( $t-2$ )					Age at dry season of agr. year ( $t-1$ )					Age cohorts (age at survey)				
in utero					0–11 months					12–23 months				
0–11 months					12–23 months					24–35 months				
12–23 months					24–35 months					36–47 months				

**Source:** Authors.

**Note:** Agr. year = agricultural year; ENN = National Nutrition Survey;  $t$  = the 2000 agricultural year, during which the ENN survey was conducted;  $t-1$  = one agricultural year before the survey;  $t-2$  = two agricultural years before the survey.

and ceiling temperatures that contribute to growth. See chapter 4 of this volume for more details about the base and ceiling temperatures used to calculate GDD. To determine the cumulative GDD at any point in time for a specific cultivation, the daily GDD since planting are summed.

*Measuring weather shocks.* To measure weather shocks, we first calculate the municipal historic mean rainfall and GDD between 1951 and 1985 for each agricultural year and wet season. We chose this time span to balance the need to use as many years of historic weather information as possible (ideally at least 30 years) with the need to exclude both (a) recent years that may have been affected by changing climate and (b) the earlier years with less-reliable data. Because information was incomplete for some months for some of our municipalities (meaning that none of the 20 closest weather stations reported data for five or more consecutive days), the average climate is based on 15 to 35 years of information. Of the rural households in our sample, 75 percent live in municipalities with at least 30 years of complete weather information between 1951 and 1985.

Weather shocks are defined based on the degree of deviation from the 1951–85 average weather—that is, when the weather variable is more than one standard deviation from its long-run mean. A municipality had a *negative* rainfall shock if the prior period's rainfall was at least one standard deviation less than the average 1951–85 rainfall. The municipality had a *positive* rainfall shock if the prior period's rainfall was at least one standard deviation more than the average 1951–85 rainfall. Thus, four types of weather-shock measurements may describe a particular period's weather: negative and positive temperature (GDD) shocks and negative and positive rainfall shocks.

Based on this measurement, a rainfall shock of one standard deviation translates to an average of about 30 percent more or less rainfall than the long-run mean during the agricultural year or its wet season. One standard deviation of GDD represents an average of about 8 percent warmer or cooler temperature than the mean.

Weather shocks also must be measured in the context of each region's distinct climate, and even within a region there is much variability. In general, however, the north is drier than the rest of the country, and the central region is colder than the rest of the country.

Comparing weather data from 1986 to 2002 with their historic means (from 1951 to 1985), the number of *temperature* shocks (both negative and positive) seems to have increased, but there has been no similar increase in *rainfall* shocks in Mexico.

Because the households were surveyed during the 2000 dry season, we use the weather during the 1999 agricultural year (October 1998 to September 1999) and the 1998 agricultural year (October 1997 to September 1998) to build our set of weather shocks, with these results:

- *Weather shocks during the 1998 agricultural year* would have affected the 1998 wet season harvests and thus agricultural income and production available to the household in 1999, the year before the household survey and weight measurements.
- *Weather shocks during the 1999 agricultural year* would have affected the 1999 wet season harvest; thus, even if the production was low, the household would not yet be feeling the effects of low harvest in October and November 1999, when the survey was conducted.

Even after a poor harvest, agricultural households do not face scarcity during the early months of the next dry season (Chambers et al. 1981). The important point is that the weather shocks during the 1999 agricultural year capture the potential changes in the prevalence of weather-dependent communicable diseases in the year before the survey.

There were more GDD shocks than rainfall shocks in our sample of municipalities during both the 1999 and the 1998 agricultural years.<sup>13</sup> Furthermore, a small number of municipalities experienced a positive rainfall shock in the 1998 agricultural year and wet season. Therefore, any coefficient estimates for the positive rainfall shocks during the 1998 agricultural cycle need to be interpreted with caution because of the small number of observations experiencing such a shock.

### ***Height-for-Age Estimation Strategy***

For a complete analysis, we need an estimation methodology to establish the link, if any, between weather shocks and our chosen proxy for childhood health: height-for-age. For the empirical analyses, we use cross-sectional individual-level data, standardizing a height-for-age Z-score (as previously discussed concerning the World Health Organization statistics) by taking several variables into account, including the following:

- The individual's height
- Weather shocks (negative or positive) in the individual's locality during the period under consideration
- Past weather shocks (negative or positive) in the same locality

- Factors that could affect height, such as household and housing characteristics
- Other factors such as gender and whether the individual participated in a supplemental nutrition program
- Location specific characteristics, or fixed effects.

From these calculations,<sup>14</sup> we can estimate the aggregate impacts of weather shocks on child height. We cannot separate these impacts from those (negative or positive) that might have occurred because of changes in consumption affecting nutrition or bouts of illnesses. However, as explained below, given the timing of the survey and the inclusion of weather shocks from the two prior agricultural years, we gain some insights about the potential channels through which the shocks affect health.

To analyze the average impact of weather shocks on child outcomes, we use the standardized height-for-age Z-score for children between 12 and 47 months of age as our measure of health.<sup>15</sup> These children were between zero and 35-months-old in the agricultural year prior to the health measurement and in utero to 23 months in the agricultural year two years prior to the health measurement. We are thus effectively measuring the effects on height of shocks experienced during the first three years of life.

Compared with weight-for-age measurements, height-for-age is not as sensitive to very short-term and immediate scarcities or illness; it would capture more chronic conditions.<sup>16</sup> However, we also can include state-level fixed effects in our estimate. The decentralized decision process in Mexico gives states the responsibility, for example, of delivering health services, water supply and sewage, and rural development and extension services (Cabrero Mendoza and Martinez-Vazquez 2000). The state-level fixed effects control for the impact of the state-based policies on health outcomes as well as any general agro-climatic conditions that vary across states.<sup>17</sup>

Besides our measures of weather shocks, we also include information in the analyses on these regressors<sup>18</sup>:

- Household composition (numbers of children, adult males, and adult females)
- Mother's characteristics (education, height, and whether she speaks an indigenous language)
- Child's characteristics (gender, whether the child has an older sibling born alive within two years of the child's birth, multiple birth, birth

order, 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<sup>19</sup>
- Housing characteristics (presence of indoor toilet, tap water, type of floor)
- Child's locality (altitude).

For a more-detailed description of these variables and their use in the analyses, see Skoufias and Vinha (2012).

Given the regional differences in the average climate, we separate the children into three regions and carry out the analyses separately. Furthermore, there is evidence that altitude and birth weight are related (Jensen and Moore 1997; Wehby, Castilla, and Lopez-Camelo 2010; Yip, Binkin, and Trowbridge 1988) and that the effects become significant at altitudes greater than 1,500 meters (m) (Yip, Binkin, and Trowbridge 1988).<sup>20</sup> To complement the regional results and to investigate whether the effects of weather shocks are different at different altitudes, we also analyze the impact for children living in low altitudes (less than 1,500 m above sea level) and for children living in high altitudes (more than 1,500 m above sea level).

The ENN dataset included 2,007 rural children between the ages of 12 months and 47 months, and our sample consists of 1,530 children. We include only the 1,882 children whose mothers had not moved in the previous two years to ensure that the weather shocks we used matched what the child had experienced. Some of the children were excluded because of missing height information (128 children), improbable Z-scores (35 children),<sup>21</sup> or incomplete information on the covariates (189 children). The children measured (and having probable Z-scores) have mothers—compared with mothers of children who were not measured—who are statistically significantly taller, more likely to speak an indigenous language, more likely to live in lower altitudes, and less likely to have running water or indoor sanitation. These differences pose a problem because those children who were not measured are different, and they may be systematically different in other, unobserved characteristics as well.<sup>22</sup>

## **Results: How Weather Shocks Affect Rural Children's Height**

### ***Effect of Positive Rainfall Shocks***

Bearing the above caveats in mind, we find that after a positive rainfall shock, children are shorter regardless of their region or altitude, although

some distinctions must be made in each category, as discussed below. A positive rainfall shock in the 1999 agricultural year or wet season is associated with lower height-for-age scores. This result held true for both a positive annual and a positive wet season rainfall shocks. (For summary tables and regressions, see Skoufias and Vinha 2012.)

The statistically significant coefficient estimates between 0.87 and 0.32 points are nontrivial because a Z-score of  $-2$  is indicative of stunting, and the average height-for-age Z-score for the children in the sample is  $-1.4$ .

***Regional and altitude distinctions.*** The biggest impact was from a positive rainfall shock during the wet season in the north. Children who experienced such a shock had an average Z-score that was 0.87 points lower than children who experienced an average amount of rain during the wet season. The statistically significant effects were also negative, albeit smaller, in the Central, Pacific, and Gulf and Caribbean regions.<sup>23</sup>

Concerning any positive rainfall shocks in the 1998 agricultural year, the results must be interpreted with caution because our sample included only a few municipalities (less than 5 percent of the sample) that had positive rainfall shocks in the 1998 agricultural year wet season. Moreover, no statistically significant impacts were found for the North, Pacific, or Gulf and Caribbean regions. Dividing the sample based on the altitude of the municipality yields similar negative results. The improbably large coefficient estimate in the Central region most likely is an artifact of few observations rather than a causal correlation.

### ***Effect of Negative Rainfall Shocks***

Negative rainfall shocks had different effects depending on the region and altitude.

***Regional distinctions.*** If the 1999 wet season was at least one standard deviation drier than average, children living in the central region were taller (with Z-scores averaging 0.7 points higher) than if the wet season was within one standard deviation of the historic mean. In the North, Pacific, and Gulf and Caribbean regions, the relationship is not statistically significant.

However, in the Pacific and Gulf and Caribbean regions, a negative rainfall shock in the 1998 agricultural year was associated with taller children.

***Altitude distinctions.*** Children living at high altitudes were 0.54 points taller if the 1999 agricultural year had been drier than normal and 0.43 points taller if the 1999 wet season had been drier than normal.

Children living at low altitudes were 0.39 points shorter if the 1998 wet season had been drier than normal.

### ***Effect of Negative GDD Shocks***

Whereas negative GDD shocks (cooler temperature) during the 1999 agricultural year are positively correlated with height-for-age in the central region as well as in high altitudes, negative GDD shocks during the 1998 agricultural year are negatively associated with height-for-age in the Central, Pacific, and Gulf and Caribbean regions as well as in high altitudes. The largest reduction is 0.72 points in the central region.

However, in the northern states, unlike most of Mexico, negative annual GDD shocks in 1998 are positively correlated with height, with the average height-for-age being 0.46 points higher after such a shock than had the shock not occurred.

### ***Effect of Positive GDD Shocks***

Positive GDD shocks (warmer temperatures) are not statistically significantly correlated with height-for-age, regardless of where the child lives or the timing of the shock. The result is consistent whether we separate the sample by geographic regions or by altitude.

It is possible that not all children experience the same kind of health outcomes from weather shocks. Skoufias and Vinha (2012) present the results when weather shocks are interacted with the sex of the child, the age cohort of the child, the educational attainment of the mother, and the household's participation in a supplemental nutrition program. The authors also present the average result for all of Mexico as well as the average results for municipalities below 1,500 m above sea level as well as the average results for municipalities above 1,500 m above sea level.<sup>24</sup>

### ***Gender Distinctions***

In this sample, although the girls' and boys' average height-for-age Z-scores are not statistically significantly different overall, they *are* significantly different when the child experienced a *positive GDD shock* in the prior wet season. Boys are shorter when the prior wet season was at least one standard deviation warmer than the mean. The coefficient estimate is larger for boys living in higher altitudes (implying a larger effect) than for boys living in lower altitudes.

Girls are statistically significantly different from the boys in low altitudes, by 0.42 points. Among girls, regardless of altitude, there are no differences between those who experienced an unusually warm year from those who did not. However, a positive GDD shock experienced *two* agricultural years before the survey (during the 1998 agricultural year) did not have a statistically significant effect on height-for-age for boys *or* for girls, suggesting that the impact of such shocks do not persist in time.

In contrast, after a *negative annual GDD shock* during the 1999 agricultural year in the low altitudes, girls were statistically significantly shorter than boys, by 0.54 points.

After *positive rainfall shocks* in the 1998 wet season, girls were also statistically significantly shorter than boys, but given the low number of children who experienced such shocks, this finding must be interpreted with caution.

### **Age Distinctions**

The age of the child at the time of the weather shock also makes a difference. *Negative rainfall shocks* in the 1999 agricultural year had a positive effect on the height of those children who, at the time of the 2000 survey, were 12- to 23-months-old and lived at high altitudes but not on older children or those in low altitudes.

In the low altitudes, a *negative annual rainfall shock* in the 1998 agricultural year was associated with taller children in the youngest cohort, and a negative rainfall shock in the 1998 wet season was associated with shorter children in the oldest cohort.

There are no statistically significant differences from *positive rainfall shocks* in the 1999 cycle by age cohort, but there *were* differences in the effects of *positive GDD (warmer temperature) shocks* in the 1999 agricultural year or wet season. Such shocks negatively affected the youngest cohort (12- to 23-months-old) but not the older children. Moreover, in lower altitudes, there is negative effect from positive GDD shocks in the 1998 wet season on the youngest cohort, but again not on the older ones.

### **Mother's Education**

Under normal conditions, on average, a mother's educational attainment (as measured by the completion of primary school) does not affect her children's height-for-age scores. However, when faced with a weather shock, the mother's educational attainment *does* affect a child's height-for-age.

In low altitudes, children from less-educated mothers were shorter after a *positive annual rainfall shock* in 1999 or a *negative wet season GDD shock* in 1998 than children with more-educated mothers. In the higher-altitude municipalities, children from less-educated mothers were taller after a *negative wet season GDD shock* in 1999 than children from more-educated mothers.

### **The PROGRESA Effect**

Another household characteristic that may affect weather's impact on health outcomes is the household's participation in some type of social protection or assistance program. Supplemental nutrition programs (such as PROGRESA and Liconsa in Mexico) try to improve childhood nutrition in the poorest households. Households participating in such targeted programs are from the poorest households in the country, which may have fewer resources available to cope with weather shocks.

Interestingly, in our sample, children in households participating in a supplemental nutrition program are statistically significantly taller in the low altitudes than children not benefiting from such programs. However, when faced with certain weather shocks, the health of children living in households receiving supplemental nutrition is statistically significantly worse than the health of children not in such programs. Because 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. More likely, the results suggest that participation in a supplemental nutrition program does not fully level the playing field in terms of child health outcomes after certain weather shocks.<sup>25</sup>

In the low altitudes, annual and wet season *positive rainfall shocks* in 1999 were associated with decreases of 0.43 and 0.57 points, respectively, in the Z-scores of children in nutritional programs compared with those not in such programs.

In the high altitudes, *negative rainfall shocks* in 1998 were associated with statistically significantly shorter children when the child's household participated in a nutritional supplement program than when it did not.

## **Discussion and Conclusions**

Weather-related events can affect the welfare of individuals either through changes in agricultural production (and therefore potentially on

consumption) or through changes in the prevalence of certain diseases and ailments associated with different weather conditions.

Exploring the consequences of weather on the health of a group of vulnerable individuals—rural children in Mexico between the ages of one and four—we find some evidence that both unusual rainfall and unusual temperature affect child's height-for-age and thus potentially their short- and long-term health and productivity. We cannot determine whether the effects derive from changes in consumption or from changes in the prevalence of diseases and ailments associated with different weather conditions, but the results suggest that potentially both pathways are important.

We observe three consistent results, as described below.

### ***Strongest Overall Impact: Positive Rainfall Shocks***

*Positive rainfall shocks in the prior agricultural year (1999) negatively affect the average height-for-age regardless of region and altitude.* However, the statistical significance and magnitude of the impact vary spatially and temporally. In the central region municipalities and in municipalities at high altitudes (above 1,500 m), positive precipitation shocks in the prior agricultural year are statistically significantly associated with lower height-for-age, whereas in the Pacific and Gulf and Caribbean regions as well as at low altitudes, it is the wet season precipitation that matters. In the north, both the annual and wet season shocks negatively affect height.

Because any potential food scarcities from a bad harvest in the 1999 agricultural year will most likely be experienced toward the end of the 2000 agricultural year, and because the height measurements were taken at the beginning of the 2000 cycle, these health effects are more likely due to changes in the prevalence of communicable diseases than from undernutrition as a result of a bad harvest.<sup>26</sup> Supporting such a conclusion, negative rainfall shocks in 1999 are associated with taller children (statistically significantly in the Central region and in high altitudes). The combination of these effects suggests that, on average in rural Mexico, weather-related illnesses become more prevalent when rainfall increases.

Furthermore, in municipalities below 1,500 m after a positive rainfall shock, children whose families participate in a nutritional supplement program are statistically significantly shorter than those who do not participate. In fact, children in low altitudes who do not benefit from a nutritional supplement are not affected at all by such a shock. Thus, in 1999, participation in a nutritional supplement program did not protect children from the effects of unusual weather. Because, in general, only the

poorest households are beneficiaries of such programs—and thus participation is nonrandom—the results suggest that poorer families simply do not have the resources that wealthier families do to protect their children from the increasing prevalence of disease following unusually heavy rains.

Such effects are not observed for the sample of children in the high-altitude municipalities, potentially because of either (a) a smaller percentage of sample households receiving supplements (10 percent versus 20 percent in the low-altitude municipalities) or (b) differences in how such shocks affect disease prevalence at different altitudes.

Because only a few municipalities in our sample experienced a positive rainfall shock in the 1998 cycle, we cannot determine whether a positive rainfall shock also potentially affects health through the consumption channel nor whether the observed effects are short-term rather than longer-term ones.

### ***Delayed Consequences: Negative GDD Shocks***

*Negative GDD shocks (cooler cumulative temperatures) during the 1998 agricultural cycle negatively affected the height measurements by the beginning of the 2000 agricultural year.* There were statistically significant decreases in the average height-for-age in both the central and southern parts of the country as well as at high altitudes.<sup>27</sup> These negative effects suggest that households may not be able to protect themselves from income fluctuations brought on by the colder-than-usual weather in these regions. Furthermore, in both the central region and the high altitudes, there was a positive correlation between a negative GDD shock during the 1999 agricultural year and height-for-age.

Together these results suggest that although the immediate effects from a negative GDD shock may be positive—potentially because of lower prevalence of communicable diseases—a year later such positive gains may have been lost because of decreased food availability in the household. That the negative impact from the 1998 shocks is observed in the central region as well as in high-altitude municipalities may reflect the lower average temperatures of these sets of municipalities. They may thus be more likely to experience freezing temperatures with such a degree of damage to crops that households cannot protect their consumption in the following year.

### ***Little to No Average Impact, with Exceptions: Positive GDD Shocks***

*Positive GDD shocks (higher cumulative temperatures) during both the 1999 and the 1998 agricultural cycles did not appear to affect the health of an*

*average child in Mexico.* That is, for our sample of municipalities and children, unusually warm weather in the two years preceding the health survey did not, on average, have statistically significant effects on health as measured by height-for-age. Any changes in the prevalence of diseases (captured by the 1998 and 1999 shock measures) or agricultural income (captured by the 1998 shock measure) were sufficiently small that households could mitigate their consequences such that no adverse effects on height were observable.

The results suggest that, in 1999, an average household could cope with intermittent higher temperatures. However, interacting the positive GDD shock with various characteristics of the child yields a more varied panorama. For example, a positive GDD shock in the 1999 agricultural cycle negatively affected only the height of boys and of children between the ages of 12 and 23 months by the end of 1999, and a positive GDD shock in the 1998 agricultural cycle negatively affected only children of less-educated mothers.

One possible explanation for a negative impact on boys is the difference in morbidity rates between girls and boys, especially among the marginally malnourished (Wells 2000). Similarly, the negative effect on the youngest cohort may stem from their greater susceptibility to illnesses such as diarrheal diseases (Kosek, Bern, and Guerrant 2003), which may increase with temperature (SEMARNAT 2007).

The statistically significant decrease in the nationally averaged height-for-age of children of less-educated mothers from a positive 1998 GDD shock may derive from those mothers' inability to smooth consumption as easily as their more-educated peers in response to the agricultural production changes brought on by warmer weather. Although we cannot determine whether or not households would be able to change their behavior enough were the increased temperatures permanent, the results do suggest that there are three specific subpopulations—boys, children between 12 and 23 months at the age of the survey, and children of less-educated mothers—whose caregivers cannot currently safeguard their children from the effects of warmer weather.

### ***Questions for Research, Questions for Policy***

Considering the available evidence to date linking childhood health to various aspects of adult well-being,<sup>28</sup> these results warrant further research into the welfare impact of weather shocks and effective policy options to reduce any negative impacts from unusual weather.

Although we cannot say how households will adapt if temperature- and rainfall-related shocks become permanent, the results do suggest that certain populations may need more resources to counter potential negative effects, at least in the transition phase to the new climatic equilibrium.

The results also raise the question of whether a “tailored” approach to designing programs to decrease the sensitivity to climate and increase rural households’ capacity is likely to be more successful than a uniform program.

## Notes

1. According to the Intergovernmental Panel on Climate Change, 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. 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).
2. For example, by planting both corn that is fast maturing but has low yields and corn that is slow maturing but has higher yields, or by planting different crops altogether (such as wheat instead of corn), depending on the prevailing weather (Eakin 2000).
3. 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 also use their savings (Paxson 1992); take loans from the formal financial sector to carry them through the difficult times (Udry 1994); sell assets (Deaton 1992); or send their children to work instead of school 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 after-the-fact adjustments in labor supply such as multiple job holding, and engaging in other informal economic activities (Kochar 1999; Morduch 1995). Baez (2006) provides a detailed summary of consumption smoothing mechanisms in developing countries.
4. Based on World Health Organization (WHO) Child Growth Standards, in the first year of life, the median length for boys increases by 25.5 centimeters (cm) and for girls by 24.9 cm. In the second year, the median lengths increase by 12.1 cm and 12.4 cm for boys and girls, respectively. In

- the third year, the median heights increase by 9.0 cm and 9.4 cm for boys and girls, respectively.
5. However, there is no consensus on the conditions for catch-up growth. Although birth order and number of siblings appear to play a role (Adair 1999; Godoy et al. 2010), the effect of economic conditions depends on the population studied. For example, Adair (1999) finds that, with improved socioeconomic conditions, some Filipino children whose growth was stunted at age 2 were no longer considered stunted by 8.5 years of age. But interestingly, Godoy et al. (2010) find that improved economic conditions are correlated with *lower* catch-up rates among the Tsimané people of Bolivia.
  6. The health status of an individual also may affect his or her wage-earning capacity and ultimately the household-level consumption expenditures. For now, we do not explore this pathway. Health also affects the consumption bundle directly in two ways: *ex ante* (for example, preventive health care) and *ex post* (for example, buying medicines to treat illness).
  7. The discussion on the impact of climate on health (in this and the following paragraph) relies heavily on Patz et al. (2003).
  8. For population-based assessment, the WHO expresses child growth survey results using Z-scores. For consistency with clinical screening, prevalence-based data are commonly reported using a cutoff value. The WHO Database on Child Growth and Malnutrition (WHO n.d.) uses a Z-score cutoff point of less than  $-2$  standard deviations to classify low weight-for-age, low height-for-age, and low weight-for-height as moderate and severe undernutrition and less than  $-3$  to define severe undernutrition. For more information, see <http://www.who.int/nutgrowthdb/about/introduction/en/index5.html>.
  9. The ENN can be accessed at <http://www.bdsocial.org.mx/>, INEGI at <http://www.inegi.org.mx/>, and the Secretariat of Health at <http://www.salud.gob.mx/> (INEGI and Secretaría de Salud de México 1999).
  10. From the ENN survey, we cannot determine whether a rural household engages in agricultural activity or what kind of agricultural practices are used. ENN is representative at the regional level and at the urban/rural level and should thus reflect the general population. Included in the sample are households with small plots practicing subsistence farming as well as those with irrigated lands and farming large areas of land. What we observe is an average impact over the whole rural population. In our sample, 86.6 percent of the rural children live in households without tapped water, and 74.5 percent do not have access to an indoor toilet, suggesting that most of the children come from very modest means.
  11. Because the agricultural year runs from October to September, the first agricultural year that we use to calculate the average weather for municipalities

- is 1951, and thus we only use the last three months of the 1950 calendar year.
12. Other important crops in Mexico are beans, which require 2,400 GDD, and sorghum, which requires 2,200–2,370 GDD.
  13. For the distribution of rainfall and GDD shocks for the 169 municipalities in our sample, see Skoufias and Vinha 2012.
  14. For the full estimation method, see Skoufias and Vinha (2012).
  15. To calculate the standardized height-for-age scores, we use WHO Anthro software for personal computers, version 3, 2009: Software for assessing growth and development of the world's children. See <http://www.who.int/childgrowth/software/en/>.
  16. The measure does not capture any differences in mortality from unusual weather.
  17. We cannot introduce municipal-level fixed effects, which would control more precisely for general agro-climatic conditions, because our weather shocks are at the municipal level.
  18. Only when analyzing the effects by participation in a nutritional program do we also include nutritional program participation as a regressor.
  19. 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 a motor vehicle.
  20. Furthermore, above 1,500 meters (m), there are some physiological impacts on humans; specifically in Mexico, it has been used as a cutoff altitude for some disease vectors. Besides the correlation between altitude and birth weight, above 1,500 m, "physiological changes due to hypobaric hypoxia are detectable" (Pollard and Murdoch 2003, 1). In addition, Hernández-Avila et al. (2006) use only localities below 1,500 m in their study on malaria in Oaxaca, citing that cases above 1,500 m are likely to have been imported.
  21. That is, their height-for-age Z-scores were either less than  $-6$  or more than  $6$ .
  22. If those who were not measured are more likely to be sick (and some of these illnesses are due to the weather), the coefficient estimates of the weather shock variables are likely to provide a lower bound of the true impact of the weather shock.
  23. The analysis considers results in five distinct regions of Mexico: North, Central, South, Pacific, and Gulf and Caribbean.
  24. As with the average impacts, there are some regional differences as to how the various shocks affect different subpopulations. These results are available from the authors upon request.

25. To determine the causal impact of a nutritional program (and the interaction of weather shocks with program participation), we would need to determine the counterfactual—that is, the health outcomes after a weather shock for children who participated in such programs had they not benefited from the programs.
26. However, it is possible that part of the impact comes from reduced food availability. For example, if the unusually high precipitation is accompanied by floods that greatly reduce the harvest, food availability could be reduced by the time of the following mid-dry season.
27. Unlike the other regions of Mexico, children in the North region were taller after a negative GDD shock in 1998, suggesting that colder weather improves agricultural production in this region. A negative GDD shock in 1999, however, is not statistically significantly associated with child height-for-age, suggesting that the shock does not affect the prevalence of diseases.
28. 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).

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Over the past century, the world has seen a sustained decline in the proportion of people living in poverty. In the past three decades alone, the rate of extreme global poverty has been halved, a remarkable trend that is expected to continue.

Amid this good news, however, are concerns that climate change could corrode or even reverse progress on poverty reduction. The resulting pressures on environmental systems from increasingly erratic weather patterns could imperil in particular the livelihoods of the rural poor, who are arguably among the first to feel the effects of such weather shocks, as well as the most vulnerable to those effects.

*The Poverty and Welfare Impacts of Climate Change: Quantifying the Effects, Identifying the Adaptation Strategies* delves into the vitally important question of the impact of climate change and surveys existing research on its potential consequences on global poverty rates. It looks closely at vulnerable rural populations in Indonesia and Mexico, where the increased frequency of weather extremes has had measureable short-term, if not immediate, effects on the farming livelihoods on which many people depend for both income and subsistence.

In viewing the effects from these country studies, the authors provide quantitative evidence on the impacts of climate change on different dimensions of household welfare, and they investigate the heterogeneity of household strategies available in coping with and adapting to climatic shocks. They draw attention to the role of policy makers to sustain those public programs that mitigate the regressive impacts of climate change, and they emphasize the need to align climate-change preparation with development objectives and continuing poverty-reduction strategies.

This book advances the consideration of key climate change effects and their implication for poverty-reduction progress during the world's transition toward a new climate equilibrium. By examining the impact of climate change on rural populations—and the effectiveness of their adaptation strategies—the authors provide a preview of the social consequences arising from a potentially volatile global problem.



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SKU 19611