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.[1] 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 macroeconomic 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.[2] 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

	Effect of climate change on average incomes (percentage change)	*Effect on poverty*	*Effect on inequality*
Bolivia[a]	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.[3]

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.[4] 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.[5]

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).[6] 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[7] 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.[8]

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 GPD 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.[9]
- *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).[10] 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.[11] This outcome contributes to cutting the world poverty rate

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

	Number of poor people (millions)			*Headcount poverty rate (%)*		
Scenarios	*2005*	*2055*	*Change*	*2005*	*2055*	*Change*
Baseline[a]	2,069.4	1,259.1	(810.3)	32.3	14.1	(18.2)
BAU[b]	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[c]	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.[12] 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[13]
- The distribution of productive endowments (such as irrigated and nonirrigated 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.[14]

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).[15] 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[16] 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.[17]
- 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).[18]

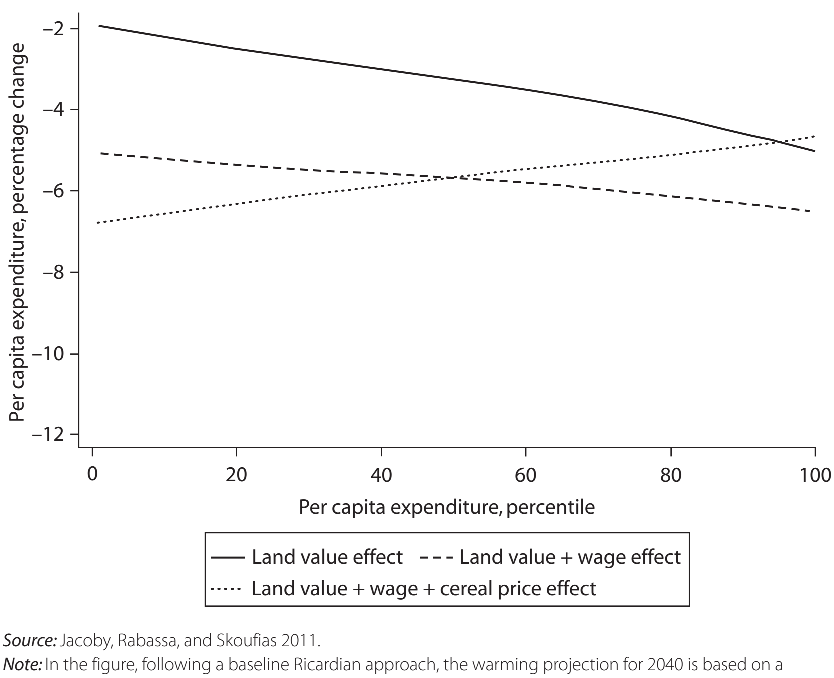
Using microdata representative for all India and following the Ricardian approach proposed by Mendelsohn, Nordhaus, and Shaw (1994), the authors estimate the impacts of climate change in 2040 on agricultural productivity and wages, taking into account adaptation (using district-level cross-sectional data) and assuming imperfect mobility of labor.[19] 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.[20]

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.[21]

- 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).[22]

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

	Base year 2004/05	*No growth 2040*	*Low growth[a] 2040*	*Medium growth[b] 2040*	*High growth[c] 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

	Low growth[a]	*Medium growth*[b]	*High growth*[c]
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.[23] 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.[24] 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[25]:

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

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:

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

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):

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

where b is the poverty-growth elasticity with respect to the mean consumption given by m.[26]

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.

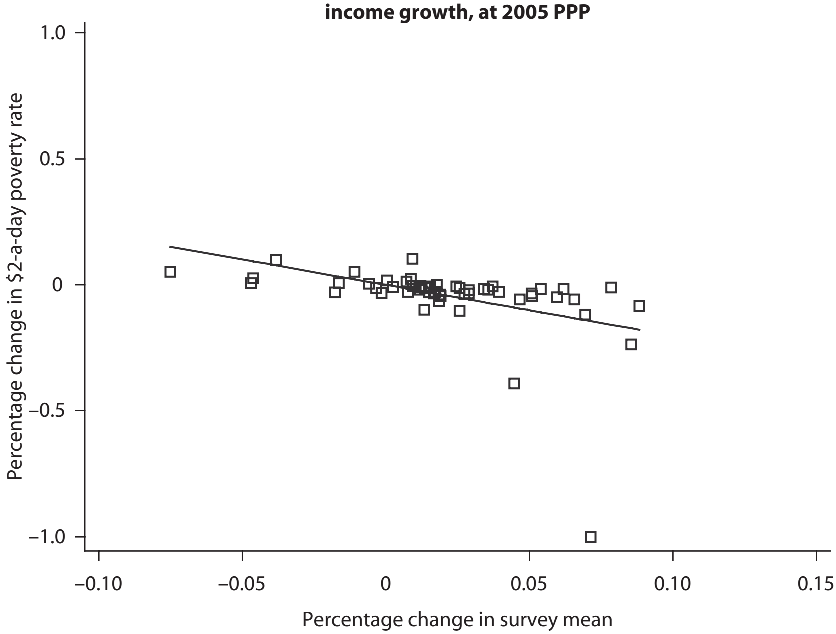
In contrast, panel b of figure 2A.1 plots the proportionate changes in the same poverty rate against the growth rate in PCE per capita. Though similar, the estimated elasticity of −1.44 (standard error of 0.60) is not as strong as before.[27] It is important to note that these estimations are based on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

Data

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

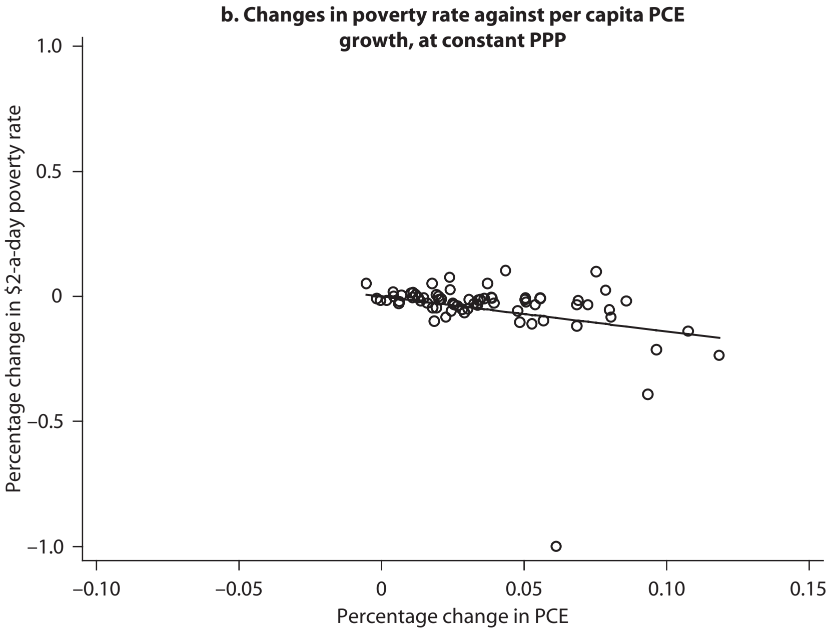
Figure 2A.1 Changes in Poverty Headcount Ratio

a. Changes in poverty rate against annual mean household income growth, at 2005 PPP



(continued next page)

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.[29] 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

Region	*Country*	*Survey dates*		*Welfare indicator*	*Region*	*Country*	*Survey dates*		*Welfare indicator*
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[a]		Cameroon	1996	2001	Expenditure
						Cape Verde	2001	—	Expenditure
Russia	Russian Federation	1993	2007	Expenditure[a]		Central African Republic	2003	—	Expenditure
						Comoros	2004	—	Expenditure
EurAsia	Albania	1997	2005	Expenditure		Congo, Rep.	2005	—	Expenditure
	Armenia	1996	2007	Expenditure[a]		Egypt, Arab Rep.	1991	2005	Expenditure
	Azerbaijan	1995	2005	Expenditure		Ethiopia	1995	2005	Expenditure
	Belarus	2000	2005	Expenditure		Guinea	1991	2003	Expenditure
	Bosnia and Herzegovina	2004	2007	Expenditure[a]		Guinea-Bissau	1991	2002	Expenditure
	Bulgaria	1994	2003	Expenditure		Gabon	2005	—	Expenditure
	Croatia	1998	2005	Expenditure		Kenya	1992	2005	Expenditure
	Estonia	1995	2004	Expenditure		Lesotho	1993	2003	Expenditure
	Georgia	1996	2005	Expenditure		Madagascar	1993	2005	Expenditure
	Kazakhstan	1996	2003	Expenditure		Malawi	1998	2004	Expenditure
	Kyrgyz Republic	1993	2004	Expenditure		Mali	1994	2006	Expenditure
	Latvia	1998	2007	Expenditure[a]		Mauritania	2000	—	Expenditure
	Lithuania	1996	2004	Expenditure		Morocco	1991	2007	Expenditure
	Macedonia, FYR	1998	2006	Expenditure[a]		Mozambique	1997	2003	Expenditure

(continued next page)

Table 2A.1 *(continued)*

Region	*Country*	*Survey dates*		*Welfare indicator*	*Region*	*Country*	*Survey dates*		*Welfare indicator*
	Moldova	1997	2004	Expenditure		Namibia	1993	—	Income
	Romania	1998	2007	Expenditure[a]		Niger	2005	—	Expenditure
	Slovenia	1998	2004	Expenditure		Senegal	1991	2005	Expenditure
	Tajikistan	1999	2004	Expenditure		South Africa	1993	2000	Income
	Ukraine	1996	2008	Expenditure[a]		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 America	Argentina-Urban	1996	2006	Income
	Jordan	1992	2006	Expenditure		Belize	1995	—	Income
						Bolivia	1991	2007	Income[a]
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
	Cambodia	1994	2007	Expenditure[a]
	Lao PDR	2002	—	Expenditure
	Malaysia	1992	2004	Income[a]
	Mongolia	2005	—	Expenditure
	Pakistan	1991	2005	Expenditure
	Philippines	1991	2006	Expenditure
	Thailand	1992	2004	Expenditure
	Vietnam	1998	2006	Expenditure

Costa Rica	1990	2007	Income[a]
Dominican Republic	1992	2006	Income[a]
Ecuador	1994	2007	Income
El Salvador	1995	2007	Income[a]
Guatemala	1998	2006	Income
Honduras	1990	2006	Income
Mexico	1992	2008	Income[a]
Nicaragua	1993	2005	Income
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.[30]

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.

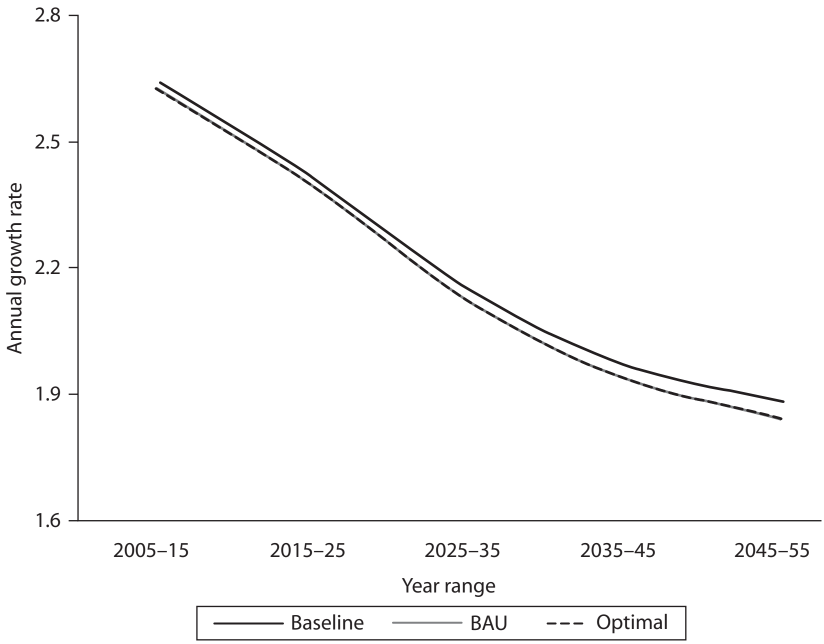
A second dataset includes per capita consumption projections for 10-year intervals from 2005 to 2055 based on the 2010 runs of the RICE model (Nordhaus 2010). From this model, we obtain growth rate trajectories for two scenarios under climate change: business as usual (BAU) and optimal abatement. The 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).[31] We modify the present investment as a function of the gross present output instead of the net present output of abatement and climate change.[32]

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.[33] 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

	Coefficient	*Robust standard error*	*t*	*p>|t|*	*95% confidence interval*	
Region						
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
Country						
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)

		2055		
	2005	*Baseline*	*BAU*	*Difference*
Region				
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
Country				
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.

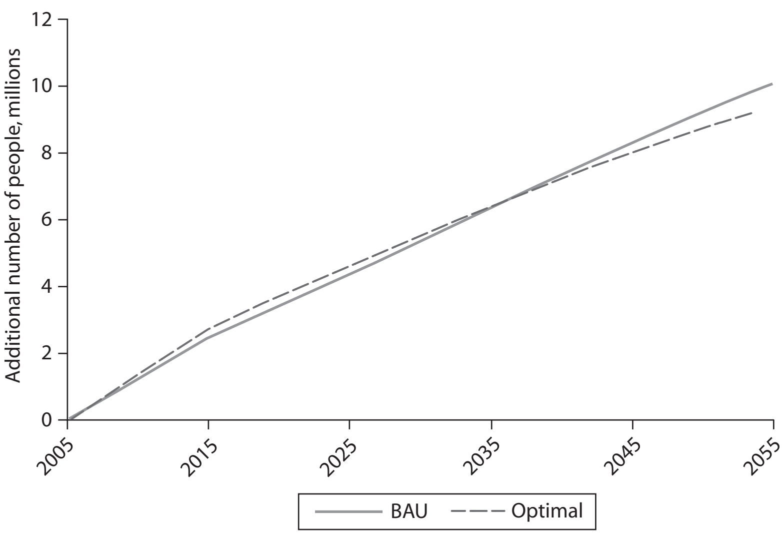
Table 2A.4 Potential Impact of Climate Change on Poverty under Baseline without Climate Change versus Optimal Scenarios, Selected Regions and Countries, 2005–55

people living on less than $2 a day, millions

		2055		
	2005	*Baseline*	*Optimal*	*Difference*
Region				
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
Country				
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.

References

Ahmed, S., N. Diffenbaugh, and T. Hertel. 2009. "Climate Volatility Deepens Poverty Vulnerability in Developing Countries." *Environmental Research Letters* 4 (3): 1–8.

Anderson, E. 2006. "Potential Impacts of Climate Change on $2 a Day Poverty and Child Mortality in Sub-Saharan Africa and South Asia." Unpublished manuscript, Overseas Development Institute, London.

Andersen, L., and D. Verner. 2010. "Simulating the Effects of Climate Change on Poverty and Inequality." In *Reducing Poverty, Protecting Livelihoods and Building Assets in a Changing Climate: Social Implications of Climate Change for Latin America and the Caribbean*, ed. D. Verner, 249–65. Directions in Development Series. Washington, DC: World Bank.

Assunção, J., and F. Chein Feres. 2009. "Climate Change, Agricultural Productivity, and Poverty." Working paper, Department of Economics, Pontifícia Universidade Católica (PUC), Rio de Janeiro.

Baez, J., and A. Mason. 2008. "Dealing with Climate Change: Household Risk Management and Adaptation in Latin America." Background paper for *Low Carbon, High Growth: Latin American Responses to Climate Change*, ed. A. de la Torre, P. Fajnzylber, and J. Nash. Washington, DC: World Bank

Bhalla, S. 2002. *Imagine There's No Country: Poverty, Inequality, and Growth in the Era of Globalization*. Washington, DC: Institute for International Economics.

Chen, S., and M. Ravallion. 2004. "Household Welfare Impacts of WTO Accession in China." *World Bank Economic Review* 18 (1): 29–58.

Cline, W. 2007. *Global Warming and Agriculture: Impact Estimates by Country.* Washington, DC: Center for Global Development and Peterson Institute for International Economics.

Datt, G., and M. Ravallion. 1992. "Growth and Redistribution Components of Changes in Poverty Measures: A Decomposition with Applications to Brazil and India in the 1980s." *Journal of Development Economics* 38 (2): 275–95.

———. 2011. "Has India's Economic Growth Become More Pro-Poor in the Wake of Economic Reforms?" *The World Bank Economic Review* 25 (2): 157–89.

Deaton, A. 1992. *Understanding Consumption*. New York: Oxford University Press.

Dell, M., B. Jones, and B. Olken. 2009. "Temperature and Income: Reconciling New Cross-Sectional and Panel Estimates." *American Economic Review* 99 (2): 198–204.

Deschenes, O., and M. Greenstone. 2007. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather." *American Economic Review* 97 (1): 354–85.

Dollar, K., and A. Kraay. 2002. "Growth Is Good for the Poor." *Journal of Development Economics* 7 (3): 195–225.

Elbers, C., J. Gunning, and B. Kinsey. 2007. "Growth and Risk: Methodology and Micro Evidence." *The World Bank Economic Review* 21 (1): 1–20.

Ferreira, F. 2010. "Distributions in Motion: Economic Growth, Inequality, and Poverty Dynamics." Policy Research Working Paper 5424, World Bank, Washington, DC.

Hertel, T., M. Burke, and D. Lobell. 2010. "The Poverty Implications of Climate-Induced Crop Yield Changes by 2030." *Global Environmental Change* 20 (4): 577–85.

Hertel, T., and S. Rosch. 2010. "Climate Change, Agriculture and Poverty." *Applied Economic Perspectives and Policy* 32 (3): 355–85.

Hillebrand, E. 2008. "The Global Distribution of Income in 2050." *World Development* 36 (5): 727–40.

Hope, C. 2006. "The Marginal Impact of CO_2 from PAGE 2002: An Integrated Assessment Model Incorporating the IPCC's Five Reasons for Concern." *The Integrated Assessment Journal* 6 (1): 19–56.

IPCC (Intergovernmental Panel on Climate Change). 2001. *Climate Change 2001: The Scientific Basis*. Contribution of Working Group I to the Third Assessment Report of the IPCC. Cambridge, U.K.: Cambridge University Press.

———. 2007a. *Climate Change 2007: The Physical Science Basis.* Contribution of Working Group I to the Fourth Assessment Report of the IPCC. Cambridge, U.K.: Cambridge University Press.

———. 2007b. *Climate Change 2007: Impacts, Adaptation, and Vulnerability.* Contribution of Working Group II to the Fourth Assessment Report of the IPCC. Cambridge, U.K.: Cambridge University Press.

Jacoby, H., M. Rabassa, and E. Skoufias. 2011. "The Distribution Implications of Climate Change in India." Policy Research Working Paper 5622, World Bank, Washington, DC.

Jacoby, H., and E. Skoufias. 1997. "Risk, Financial Markets, and Human Capital in a Developing Country." *The Review of Economic Studies* 64 (3): 311–35.

Kelly, D., and C. Kolstad. 1999. "Integrated Assessment Models for Climate Change Control." In *The International Yearbook of Environmental and Resource Economics 1999/2000: A Survey of Current Issues*, ed. H. Folmer and T. Tietenberg. Cheltenham, U.K.: Edward Elgar.

Kochar, A. 1999. "Smoothing Consumption by Smoothing Income: Hours-of-Work Responses to Idiosyncratic Agricultural Shocks in Rural India." *The Review of Economics and Statistics* 81 (1): 50–61.

Kraay, A. 2006. "When Is Growth Pro-Poor? Evidence from a Panel of Countries." *Journal of Development Economics* 80 (1): 198–227.

Mendelsohn, R., W. Nordhaus, and D. Shaw. 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis." *American Economic Review* 84 (4): 753–71.

Menon, N. 2009. "Rainfall Uncertainty and Occupational Choice in Agricultural Households of Rural Nepal." *Journal of Development Studies* 45 (6): 864–88.

Morduch, J. 1995. "Income Smoothing and Consumption Smoothing." *Journal of Economic Perspectives* 9 (3): 103–14.

Nakićenović, N., and R. Swart, eds. 2000. *Special Report on Emissions Scenarios: A Special Report of Working Group III of the Intergovernmental Panel on Climate Change*. Cambridge, U.K.: Cambridge University Press.

Nordhaus, W. 1993. "Reflections on the Economics of Climate Change." *Journal of Economic Perspectives* 7 (4): 11–25.

———. 2010. "Economic Aspects of Global Warming in a Post-Copenhagen Environment." *Proceedings of the National Academy of Science* 107 (26): 11721–26.

Paxson, C. 1992. "Using Weather Variability to Estimate the Response of Savings to Transitory Income in Thailand." *American Economic Review* 82 (1): 15–33.

Ravallion, M. 1997. "Can High-Inequality Developing Countries Escape Absolute Poverty?" *Economics Letters* 56 (1997): 51–57.

———. 2001. "Growth, Inequality and Poverty: Looking Beyond Averages." *World Development* 29 (11): 1803–15.

———. 2003. "Measuring Aggregate Welfare in Developing Countries: How Well Do National Accounts and Surveys Agree?" *The Review of Economics and Statistics* 85 (3): 645–52.

———. 2007. "Inequality Is Bad for the Poor." In *Inequality and Poverty Re-examined*, ed. S. Jenkins and J. Micklewright, 37–60. New York: Oxford University Press.

Ravallion, M., and S. Chen. 1997. "What Can New Survey Data Tell Us about Recent Changes in Distribution and Poverty?" *The World Bank Economic Review* 11 (2): 357–82.

Rosenzweig, M., and H. Binswanger-Mkhize. 1993. "Wealth, Weather Risk, and the Composition and Profitability of Agricultural Investments." *The Economic Journal* 103 (416): 56–78.

Stern, N. 2007. *The Economics of Climate Change: The Stern Review*. Cambridge, U.K.: Cambridge University Press.

Udry, C. 1994. "Risk and Insurance in a Rural Credit Market: An Empirical Investigation in Northern Nigeria." *The Review of Economic Studies* 61 (3): 495–526.

UN (United Nations). 2009. *World Population Prospects: The 2008 Revision*. New York: UN.

World Bank. 1990. *World Development Report 1990: Poverty*. Washington, DC: World Bank.

———. 2010a. *Natural Hazards and Unnatural Disasters: The Economics of Effective Prevention*. Washington, DC: World Bank.

———. 2010b. *World Development Indicators 2010*. Washington, DC: World Bank.