Essays in Climate and Development

by

Roberto Guerrero Compeán

B.A. Political Science, Institut d'Études Politiques de Paris (2003)
B.A. Economics, Universidad Autónoma de Nuevo León (2005)
M.C.P. International Development, Massachusetts Institute of Technology (2008)

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Author ....
Department of Urban Studies and Planning
20th August, 2013

Certified by ....
Karen R. Polenske
Peter de Florez Professor of Regional Political Economy
Dissertation Supervisor

Accepted by ....
JoAnn Carmin
Professor of Environmental Policy and Planning and Chairwoman, Ph.D. Committee
Department of Urban Studies and Planning

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Abstract

This dissertation is a collection of three essays on environmental policy and empirical development economics, unified in their underlying inquiry of the welfare effects of climate in Mexico.

The first chapter presents evidence on the relationship between exposure to extreme temperatures and precipitation and mortality, as well as the relationship between severe weather and agricultural income and crop production in the country, using random year-to-year variation in temperature. Estimates suggest that exchanging one single day with an average temperature for one day with extreme temperature increases the crude mortality rate by 0.15%. The impact is spatially and temporally heterogeneous: the extreme heat effect on death is three times larger in rural areas than in urban areas, while its effect on agriculture is significantly larger if it takes place during the agricultural growing season.

The second essay is an analysis of the impact of future climate change on death in Mexico. Estimates suggest that in the absence of any future effective mitigation or technology adaptation, climate change leads to a 4 to 9% increase in the annual mortality rate during the 21st century. I show that climate change disproportionately affects vulnerable groups, particularly children and rural households, whose mortality rates are estimated to increase by 19% and 40% respectively. Overall, by the end of the century climate change will lead to a loss of more than 3.1 million life-years per annum (equivalent to one life-year lost every ten seconds.)

The third essay makes the case for the effectiveness of targeted government interventions to mitigate the negative impact of weather-induced income shocks. I show that El Niño- and La Niña-related severe meteorological conditions lead to sharp declines in consumption and welfare outcomes, particularly among the poor, and more specifically in female-headed and indigenous households. Estimates suggest that the provision of a safety net significantly raises expected utility by smoothing consumption and reducing inefficient behaviors *ex post.*

Thesis supervisor: Karen R. Polenske
Title: Peter de Florez Professor of Regional Political Economy

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Chapter 1. The Welfare Impact of Extremes: Evidence from Random Fluctuations in Weather

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To my mother,
who sacrificed so much
to give me an education

Climate [is] inconceivably more important than everything one has taken to be important so far.

Friedrich Nietzsche, 1888
Ecce homo

Il n'y a pas de route royale pour la science et ceux-là seulement ont chance d'arriver à ses sommets lumineux qui ne craignent pas de se fatiguer à gravir ses sentiers escarpés.

Karl Marx, 1872
Das Kapital
Preface to the French edition

Introduction

1 Problem Significance

Mexico is a country that is exceptionally vulnerable to extreme weather patterns. What is distinctive about Mexico is its highly heterogeneous climate and ecosystems. Large portions of the country are located around so-called convergence zones, areas where opposing prevailing winds come together and drastically affect precipitation patterns. It lies squarely within the hurricane belt, and all regions of both of its coasts are susceptible to severe storms almost half of the year. Its pronounced topography, which ranges from rugged mountains and low coastal plains to high plateaus and deserts, leads to strong spatial and temporal climate contrasts and varied forms of vulnerability, which are usually exacerbated by poverty and underperforming institutions. Of Mexico's 195 million hectares of land, 85% is considered semi-arid, arid, or very arid, with climates characterized by low, seasonal and highly variable rainfall. Overall, 88 million people (roughly 8 out of 10 Mexicans) and virtually all the poor are exposed to some type of climatic risk, according to the national government (see Figures 1-4.) Most troubling, global warming and anthropogenic climate change are making weather more severe and less predictable, which, as Figure 5 shows, leads to an increase in the frequency of natural disasters, exacerbating risk at an unprecedented pace (O'Brien & Leichenko 2000, Ministry of Social Development of Mexico 2010, 2012.)

It is important to understand the nature of the risks from climate, where natural and human systems are likely to be most vulnerable. In particular, either as a result of Mexico's remarkable ecogeography or due to climate's superimposition on existing vulnerabilities inherent in Mexico's socioeconomic and institutional environment, there is a long history of research about climate in Mexico and its impact on the population, particularly on the poor. Historically, much of the seminal work on climate and its human impact has employed Mexico as a case study. Already at the dawn of the 19th century, Alexander von Humboldt, a Prussian geographer, was arguably the first proponent of investigating into the structure and social situation of the population and the health system and the role climate plays in it, using Mexico as a case study.[1] A century later, Ellsworth Huntington (1913) would be the first to develop a theory of climate change using Mexico as a reference to illustrate regional meteorological fluctuations.[2] For almost a century, the issue of climate has laid firmly both in the academic discourse and the political milieu, from paleoclimatology and the first greenhouse effect theories in the 1930s and 1940s to aerosol pollution and ozone depletion in the 1960s and 1970s to the establishment of the Intergovernmental Panel on Climate Change in 1988. Nonetheless, the acceleration of anthropogenic global warming and the increasing evidence of its impacts has led to an explosion of interest in the climate process across disciplines within and beyond climate science. As a result of empirical innovations or the development of new theoretical frameworks or methodological formulations, recent works have concentrated in more textured research approaches and shed light on key socioeconomic issues in which the role of climate is central, at least for the Mexican case: studies range from how climatic conditions affect the agricultural system and the composition of farmers' resilience (Appendini & Liverman 1994, Gay et al. 2006), to the extent to which the structure of the economy and market distortions exacerbate climate vulnerability (Gordillo & Rello 1980, O'Brien & Leichenko 2000), to the effect of weather on precipitous institutional change, the intersection of climate and political power, and the role of the state (Eakin & Lemos 2006, Florescano 1980, Liverman 1990), to uncertainty, innovations, incentives and adaptation constraints in a changing climate, both in urban and rural areas (Eakin 2006, Ministry of Social Development of Mexico 2012), to the role of climate in cultural evolution (Hoddell, Brenner & Curtis 2007.)

From a policy standpoint, this rich body of literature raises an important overarching question: Who is vulnerable to the multiple environmental changes underway,

[1] Von Humboldt's expedition to Latin America laid the foundation of modern physical geography and meteorology. In his *Essai politique sur le royaume de la Nouvelle-Espagne* (1811, p. 270-271), he asserted that "a country's physiognomy, its mountain ranges, the extension of its highlands, elevation, and how it determines temperature, is intrinsically associated with the progress of the people and the welfare of its population." [*La physionomie d'un pays, l'agroupement des montagnes, l'étendue des plateaux, l'élévation qui en détermine la température, a les rapports les plus essentiels avec les progrès de la population et avec le bien-être des habitans.*]

[2] For a historical synthesis of the early research of climate in Mexico, see Metcalfe (1987.)

where, and why? Traditional welfare research draws on theories of climate vulnerability and economic specialization from the disaster management, environmental change and development studies to answer this question (Birkmann 2005.) However, many empirical works, especially on developing countries where data accessibility is often inadequate, unintentionally overlook the spatial variability of the different types of vulnerability and of their relationships. Some scholars have outlined that "vulnerability rests in a multifaceted coupled system with connections operating at different spatiotemporal scales" (Turner et al. 2003, p. 8076), while acknowledging that "we have a limited understanding of how changing socio-economic and environmental conditions affect vulnerability [and] a more precise idea of how to integrate the time and spatial dependency of vulnerability into measurements tools" (Birkmann 2005, p. 6) is indeed still missing. Moreover, scholars have rarely attempted to examine comparatively the microeconomic effect of local climate shocks in regional and national contexts. Similarly, the fact that some groups are more vulnerable than others needs to be recognized (O'Brien & Leichenko 2000.) Underlying this vulnerability asymmetry is the inability of (mostly poor) families to cope with the negative effects of weather shocks through formal savings, credit and insurance markets, which are rarely functional for them. The poor are thus left with a variety of alternative informal mechanisms that provide inadequate risk-coping capabilities at a very high cost for their families, thus posing serious consequences for their wellbeing (Paxson 1992, Townsend 1994.) Equally concerning from a methodological point of view, a body of empirical climate research from heterogeneous disciplinary perspectives inadequately covers the complex nature of weather patterns by assuming straight line changes in climate and paying little attention to the disproportionate impact of extremes. Failure to consider the complexity of the climate process renders these models, regardless of carefully devised methodologies, foundationally fragile in their conclusions.

2 General Objective and Focus

These Essays in Climate and Development are an effort to overcome the aforementioned limitations, guided by the primary question of why, within the same region, similar extreme climate patterns and weather shocks lead to dramatically different welfare impacts on the population, and through which mechanisms they can be mitigated.

To answer this question, I specifically focus on three condensed issues: through what mechanisms does the structure of local economies mediate the impact of welfare and to what extent do climate extremes affect human health? What is the welfare cost of climate change for both the rural and urban localities and what are the vulnerable groups that will be disproportionately affected by global warming? How effective can targeted state interventions be in insulating poor households from weather-induced income shocks and reducing their need to resort to costly *ex post* risk-coping strategies?

Although the complexity and relevance of these questions lend themselves to be answered in three separate essays, each one relying on complementary theoretical frameworks and innovative methodologies that isolate the effect of weather from other variables, the essays collectively fit within a broader narrative on the underlying welfare effects of climate in Mexico. The initial essay, *The Welfare Impact of Extremes: Evidence from Random Fluctuations in Weather*, concentrates on the relationship between extreme weather and welfare, highlighting its human health, food security and agricultural dimensions. From there, the second essay, *Weather and the Coming Death of Mexico's Poor: A Regional Analysis of the Cost of Climate Change*, builds on Essay 1's findings and leads to study climate change and how future global warming trends are posed to aggravate vulnerabilities, particularly for the rural poor. This in turn transitions into the third essay, *Climate Shocks, Safety Nets, and Shielded Poor: Experimental Evidence from Rural Mexico*, a discussion on the sources of vulnerability for the poor, the risk-coping instruments they resort to in the event of a climate shock, and the evaluation of development assistance as an effective climate vulnerability-mitigation mechanism.

3 Theoretical Grounding and Contributions

Although both the conceptual framework and the empirical strategy of this dissertation are grounded on economic theory and microeconometric techniques, my investigation of climate dynamics is not dominated by one particular field, but rather, of necessity, informed by multiple disciplines. The essays necessarily sit at the intersection of four mutually supportive themes: epidemiology, agronomy, climatology, and program evaluation.

Suffice it to say for the sake of brevity, that climate at its most extreme simultaneously exacerbates the disease environment and depresses agricultural output and yields, disproportionately affecting rural households through their weather-contingent incomes (IPCC 2012.) These negative effects, furthermore, are likely to become more severe as anthropogenic greenhouse gas emissions cause higher temperatures and increased precipitation over the coming decades, making it more difficult to maintain and improve current levels of population welfare (WHO 2009.) As a result, in order to protect poor and vulnerable households from substandard living conditions resulting from severe weather, it is critical to determine what the most cost-effective policymaking approaches at the government's disposal for tackling vulnerability are, especially when there is pressure to cut programs that prevent people from falling below basic standards of health and welfare (Banerjee & Duflo 2011.)

Needless to say, I am not the first to look at the human dimension of climate dynamics. This is an area that is well traveled and a considerable amount of work has been done over the past three decades across many disciplines, from geography, meteorology and ecology to anthropology, economics, political science, environmental planning and public health. However, this dissertation is differentiated in at least four significant ways from most others who write about the general topic of climate, as I argue below.

3.1 Accounting for Non-Linear Asymmetric Relationships

First, this dissertation fundamentally departs from previous research in the way that climate is approached. I eliminate a strong assumption that has been made in many studies across the social sciences. On the whole, it seems fair to say that the study of climate in the social sciences rarely accounts for nonlinear asymmetric relationships between weather and a range of agricultural and welfare outcomes. These nonlinear relationships may be concealed when, for example, daily observations are averaged into monthly or seasonal variables (Schlenker & Roberts 2009.) On the face of it, the neglect is surprising, given the serious misspecification and omitted variable bias problems this omission causes (Sinclair & Seligman 1996, 2000, Long et al. 2005.)

A large body of work on Mexico, including recent studies, makes use of monthly and even seasonal and yearly climatic data (Aguilar & Vicarelli 2011, Andersen & Verner 2010, Conde et al. 1997, Liverman 1990, Vicarelli 2011.) Unfortunately, this is not an idiosyncrasy of research on Mexico. Studies for both developed and other developing countries, spanning different disciplines and employing different methods, have the same shortcoming. Examples include Eng and Mercer (1998), Glass et al. (1982), Larsen (1990), O'Brien (2000), Ramal et al. (2009) and Rifakis et al. (2005.)

I emphasize throughout these essays that the temporal aggregation done in these and other studies is a very risky practice due to the nonlinear effects of weather. Epidemiologists have shown that a *J*- or *U*-shaped curve has been found appropriate to describe the association between weather and death, with elevated mortality being observed at temperature extremes and relatively lower mortality at moderate temperatures (Basu & Samet 2002, Curriero et al. 2002, Huynen et al. 2001, Kunst, Looman & Mackenbach 1993.) Similarly, agronomists have shown that most crops undergo severe abiotic stress at very high or very low temperatures and precipitation levels, which disproportionately increase the likelihood of crop loss (Gómez Rojas & Esquivel Mota 2002, Neild & Newman 1990, Wang, Vinocur & Altman 2007.)

There are some fierce debates in the literature concerning the challenges of capturing the true effects of particular weather events based on data that by construction lead to inaccurate estimations. The richness and high frequency of my data allows me to solve this problem of controvertible evidence. I introduce two approaches from the agronomy literature to model the nonlinearity of climate. One approach, carried out in Essays 1 and 2, is to distribute all the daily temperature and rainfall estimates in a given year over small intervals in order to maintain weather variation in any given specification, thus accounting for nonlinear effects. Another approach is to convert daily temperatures into degree-days, which represent heating or cooling units (Hodges 1991, Grierson 2002.) The effect of heat or cold accumulation is nonlinear since temperature must be above a heat threshold or below a cold threshold. I use this strategy in both Essays 1 and 3.

3.2 Identifying Effective Strategies for Causal Relationships

The fields of environmental and development planning are chronically lacking strong empirical evidence. Observational studies typically carried out in these disciplines may be strongly suggestive, but do not carry the same empirical weight as a research framework that acknowledges the identification problem because they are unable to offer a definitive causal picture.

In effect, a problem that has plagued these and other social science fields for years is that of identifiability. Observational studies typically attempt to reduce bias by simply using regression with controls for confounding variables. Often, the claim is that observational research designs isolate cause and effect. But far from serving as "evidence" of causality, the interpretation of coefficients in such a regression framework does not necessarily have any behavioral implication. As a result, observational research designs cannot reliably identify the effects of particular phenomena or policies in the face of complex and multiple channels of causality (Banerjee & Duflo 2009.) To attribute causality, a clearly labeled source of identifying variation in a causal variable, and the use of a particular empirical methodology to exploit this information is required (Angrist & Krueger 1999.) This identification strategy is absent in observational studies.

My study, on the contrary, directly puts the identification problem front and center. I recognize that both climatic and economic processes often lead to simultaneity, so that exogenous variation is required to learn about causal relationships from information capturing climate patterns and household behavior. This is an important consideration for two explicit reasons. On the one hand, climate variables are correlated with other variables, such as infrastructure, urbanization, and the structure of the economy. However, if critical variables correlated with climate are omitted from the empirical specification, the climate variables are likely to pick up non-climate effects and lead to biased estimates and predictions (Schlenker & Roberts 2009.) On the other hand, the question of whether poverty alleviation programs are effective vulnerability-reduction mechanisms needs to recognize that program recipience is rarely, if ever, random. By definition, poverty alleviation programs are implemented in poor communities and, as a result, vulnerability may be higher in the areas where the program operates. Observational analyses might confound the effect of the program with the economic, behavioral, and political institutions that hinder development in the first place. Without an identification strategy, the researcher could only establish a correlation between policies and vulnerability outcomes at best.

I overcome these problems in my study using rigorous methods and the appropriate data. The empirical approach I employ in all three essays is based on panel data analysis and, due to the randomness of climate patterns, it seems reasonable to presume that weather fluctuations are orthogonal to unobserved determinants of mortality, agricultural outcomes and other welfare measures I study. Deschênes and Greenstone (2011) argue that there is reason to believe that such an identification strategy is valid. Similarly, to assess the impact of a targeted state intervention on poor rural Mexican households in the context of severe weather, my identification strategy in Essay 3 draws on the fact that the rollout of the program was phased and that, due to this phasing, random program assignment was introduced. The exogenous variation caused by random program assignment created two groups (recipients and non-recipients) that are probabilistically similar to each other in expectation. Under such conditions, as explained by Shadish, Cook and Campbell (2002, p. 13), "any outcome differences that are observed between those groups at the end of the study are likely to be due to treatment, not to differences between the groups that already existed at the start of the study", hence providing internally valid estimates of the causal effect.

3.3 Overcoming Data-Driven Credibility Obstacles

Compared to most of the social-science research on climate in Mexico, the empirical specifications of this study are fed using high-resolution, well-calibrated data, which is critical to design and execute effective and targeted policy responses and long-term adaptation programs.

Although important modeling advances have occurred over the past several years, high-frequency data from many general circulation models have been inaccessible or, at the very least, not openly available. As a result, researchers continue to employ data developed from previous versions of such models, compromising accuracy, precision, and inter-comparability. Today, models with 2-degree-gridded are routinely used, yet recent climate research production on Mexico has examples of climate simulations with results on a 4 by 5 latitude/longitude geographic grid. This is roughly equivalent to a 400 km by 500 km grid, a very coarse resolution for regional impact studies. At this resolution, it becomes challenging to project regional impacts. Liverman & O'Brien (1991, p. 354) argue that "coarse scales make it difficult to allocate climate changes to specific locations and tend to neglect some of the important sub-grid scale weather patterns." To complicate matters, the temporal resolution of data readily available is typically inadequate, with significant portions of data expressed as monthly averaged values (IPCC 2013.) For a variety of climate models, daily predictions are not available on a subnational scale over the course of the entire 21st century (Deschênes & Greenstone 2007.) As I discussed in subsection 3.1., this periodicity is problematic because if the impact of climate is nonlinear, averaging over time dilutes the true climate response. This consideration is particularly important when considering large, non-marginal changes in climate, now expected as a result of global warming (Schlenker & Roberts 2009.)

Having those issues in mind, the atmospheric component of the global circulation model I employ in Essay 2 for my analysis has daily temperature and precipitation data at an improved surface resolution of about 295 km by 278 km at 45 degrees of latitude. Similarly, my observed climate dataset is constructed at a 3-hour temporal resolution (eight data points per day) with a spatial resolution 32 km at the lowest latitude. Overall, the new finer-scale climate dataset I developed allows me to carry out more accurate model predictions, both at the national and regional levels, than most of the previous empirical specifications in the literature. In effect, a significant contribution of my study to the regional science literature is the credible identification of important regional weather patterns and its effects on development outcomes and particular vulnerable groups across time and space.

Another issue that my data overcome and that is typically encountered in the climate impact literature is that climate change models are often unreliable to make projections of future climate change and unable to replicate current climate and climate variability (Liverman & O'Brien 1991.) Specifically, the IPCC acknowledges that many climate change models show significant errors in the simulation of El Niño-Southern Oscillation (ENSO) (Randall et al. 2007.) This is of particular relevance to climate analysts conducting research on Latin America, given that ENSO has a wide range of effects on Mexico (Magaña et al. 2004.)

Research shows that the North American Regional Reanalysis (NARR) model, which I employ in Essay 1 to construct observed temperature and precipitation data, meets this challenge and simulates the current climatic state with a high degree of fidelity, representing accurately extreme weather event patterns over the North American Region (NOAA, 2012.) In order to determine the ability of NARR to simulate large scale circulation patterns, Mesinger et al. (2006) compare the NARR precipitation for January 1998 (when the El Niño effect was underway) with observed precipitation. Their comparison shows that over land there is an extremely high agreement between NARR and observed precipitation, even over the complex western topography of Mexico.

Finally, in Essay 3 I effectively integrate heterogeneous data sources, by merging this climate dataset with a large panel of rural households in 506 Mexican communities that were part of the original impact evaluation of Mexico's Education, Health, and Nutrition Program. With these data, the empirical framework becomes remarkably powerful in its ability to measure climate adaptation and vulnerability mitigation as a result of a specific public intervention. Overall, this study is one the first large-scale empirical investigations linking with methodological rigor weather and welfare outcomes for a developing country.

3.4 Challenging Conventional Wisdoms

The conventional explanation for the ineffectiveness of government-led anti-poverty policy is challenged by my research findings. A common piece of received wisdom about development assistance policy, particularly attractive to market ideologues, is that safety nets and poverty-alleviation schemes are the opiates to economic growth. Many vocal *laissez-faire* economists argue that poor countries around the world get massive amounts of development assistance and yet they remain just as poor. Development aid, so the critique goes, stalls development and perpetuates poverty in a dysfunctional cycle (Bauer 1972, Easterly, 2001, 2009.) Africa is the poster child of this anti-poverty policy rhetoric: millions of dollars in development funding have been focused there, but welfare remains dismally low. The neoliberal sweeping recipe against the ills of aid policy is, of course, to let markets be free so that people can find their own ways to solve their problems and engage in poverty-reducing economic activity (Easterly 2006.)

This is a compelling hypothesis. But is it true?

The argument, on the one hand, is problematic because it ignores the counterfactual that perhaps Africa would be in a worse state in the absence of poverty alleviation efforts. On the other hand, although development assistance, in general, and safety nets, in particular, are sometimes characterized with a strong element of caricature, portrayed as evils that render the poor dependent, passive, and helpless,[3] I find that this diagnosis is doubly misguided: development assistance can be effective to adjust the poor's expectations, both individually and collectively. My research illustrates that the poor are conscious agents, and precisely because they do not have many resources at their disposal, they are sophisticated decision-makers. In spite of credit, insurance and other critical markets not functioning for them, the poor are capable of coping, adjusting, and adapting to a variety of shocks.[4] As I demonstrate in this dissertation,

[3] For example, a February 3rd, 2012 article on the *New York Times* quoted Newt Gingrich, a U.S. politician, as saying that "the 'genuine conservative' position is that the 'safety net is actually a spider web [that] traps people in dependency."

[4] The adaptation process is not perfect. The poor are not rational agents due to a set of behavioral biases. Duflo (2012) does an excellent summary of these biases and the logic behind them: some biases are economic. Poverty makes people overly risk averse, to the point of foregoing economic opportunity. Some are institutional. The non-poor do not have to worry about putting thought to critical decisions in their lives (from immunization and disinfection to schooling and insurance) because the institutions within which they live are set up to do the job for them. The poor, with no one guiding their choices, are entirely responsible for every aspect of their lives. As she illustrates, it is easier for a poor person in a sub-Saharan African village to go to school, get vaccinated, drink clean water or be insured than for a rich person in a Western city not to. Some are psychological.

well-designed development schemes may fine-tune these behavioral decisions. In Essay 3, I show that the provision of a modest safety net for the most vulnerable serves as a shield against unexpected shocks, leads to significant welfare changes, and, as a result, induces corrective behavioral decisions that offsets the propensity to undertake risky strategies that compromise social and economic well-being. This is an extremely important finding that runs exactly counter to basic assumptions of traditional economic theory: small changes to incentives (in the form of a modest safety net in this case) nudge people into making different decisions than they would otherwise have done.[5] When designed correctly, these nudges can yield decisions that improve people's overall welfare.

My study also offers another radical shift in perspective regarding the poor performance by the state as a purveyor of development. Skeptics of development policy have clear structural objections to the effectiveness of government as a safety net provider. Libertarians claim that the provision of aid opens the floodgates of dependency, corruption, kleptocracy, underdevelopment, and weakened local institutions, ultimately perpetuating poverty, the thesis goes, because a lump-sum transfer does not change the incentives at the margin to invest in the economy (Easterly 2007, Moyo 2009.) Along these lines, Moss, Pettersson and van de Walle (2006, pp. 14-15) argue that "large aid flows can result in a reduction in governmental accountability because governing élites no longer need to ensure the support of their publics and the assent of their legislatures when they do not need to raise revenues from the local economy, as

With so many difficult decisions to make by themselves, the poor may believe they have less control, or opt to do nothing in order to avoid making a mistake. They are well aware that they do not have all the information they need to make a thoughtful decision, but also understand that collecting this information comes at a cost. In addition, behavioral research has shown that the poor are time-inconsistent and find difficult to resist to immediate temptation, often postponing costs in preference for wellbeing in the present, regardless of the impact that such a decision has on their future. Some are sociological. A major asymmetry between developed and developing countries is that for the poor, the basic presumption of trust, instrumental for most social interactions, is lacking. The absence of complete markets, transparency and basic property rights cannot warrant trustworthy behavior and is prone to exploit vulnerabilities.

[5] The notion that the poor's decision-making process may be suboptimal and non-monotonic contests the libertarian conviction that, regardless of the many difficulties they face on a daily basis, the poor are rational agents. It is because of individual rationality, the argument goes, that the poor are in fact the best judges of what is in their best interests, so anti-poverty policies are by construction futile.

long as they keep the donors happy and willing to provide alternative sources of funding."

Colored clichés from the right often purport government as the *fons et origo* of economic hindrance. The ideological hostility towards the state as a vital anti-poverty policy stakeholder and the neglect of government interventions as positive for the destitute is detrimental to archetypal notions of development and justice and the amelioration of the lives of the poor. A thorough reading of economic history illustrates the successful contributions and deep involvement of government in many aspects of economic and social policy (Amsden 1989, 2001, Chang 2002.) The time I spent on the ground working with program designers and community workers in rural Mexico was equally illuminating to debunk this fallacious reasoning. I found that while corruption, political patronage, clientelism and abuse of power are serious issues obstructing program targeting and operational efficiency, they can be overcome through reasonably modest reform. A program's *modus operandi* containing basic provisions related to transparency, access to information, community involvement mechanisms and simple legal provisions against political use might be insufficient to deter ulterior political incentives. However, as I document in Essay 3, my research shows that these safeguards facilitate program effectiveness and feasibility, even in the absence of complex reform processes. Mexico's Education, Health, and Nutrition Program, which I evaluate, is a good example of an institutional design accounting for these considerations (Levy 2006, De la O 2007.)

4 Specifics of the Dissertation and Overview of Findings

For each essay, I outline the significance of the research and its relevance to the broader vulnerability and climate discourses. I provide a detailed review of the existing literature in order to discuss the evolution and state of the art in relevant works that bridge climate, vulnerability and welfare. Along with this synthesis, I introduce key concepts and current strategies to study climate impacts. I proceed to set out the conceptual framework, assessing the advantages and limitations of different theoretical perspectives. I present the epistemological and methodological reasons why the models I adopt possess the capacity to overcome important deficiencies of existing research. Then, I explain how each concept in my theories is operationalized, as well as the sources of my data and methods of variable construction. Next, I frame my econometric strategy, justify its adequacy and present my research findings, which are organized into two to three subsections. Each essay concludes with a succinct restatement of the subject matter, followed by a brief summary of high-level contributions, key empirical considerations and outcomes and their policy implications, as well as suggested avenues for future work.

In *The Welfare Impact of Extremes: Evidence from Random Fluctuations in Weather*, I analyze the causal relationship between exposure to extreme temperatures and precipitation and mortality, as well as the relationship among severe weather, agricultural income and crop production in the country. I use data for all 2,454 municipalities of Mexico for the period 1980-2010. Overall, I find that extreme heat significantly increases mortality, while the health effect of extreme cold is generally trivial.

In particular, I show that exchanging one day with a temperature of 16-18°C for one day with temperatures higher than 30°C increases the crude mortality rate by 0.15%, a result robust to several model specifications. I also find that the extreme heat effect on death is significantly more acute in rural regions, leading to increases of up to 0.2% vis-à-vis a 0.07% increase in urban areas. The timing of climate extremes is relevant: I show that if a weather shock takes place during the agricultural growing season, the effects on mortality and agricultural output, productivity, prices, and crop yields are large and significant, but not so if such shocks occur during the non-growing season.

In *Weather and the Coming Death of Mexico's Poor: A Regional Analysis of the Cost of Climate Change*, I estimate the impact of climate change on death in Mexico by using random year-to-year variation in temperature and a coupled atmosphere-ocean general circulation model. In the absence of any future effective mitigation or technology adaptation, I find that climate change leads to a 4-9% increase in the annual mortality rate during the 21st century. I find that climate change will disproportionately affect vulnerable groups. My analysis points to a 11% increase in annual mortality rate among seniors between the ages of 70 and 74, while the annual mortality rate for infants and young children is expected to increase by 19%. I show that those who have the fewest assets (and who have contributed least to climate change) will be hit the hardest: by the end of the century, annual mortality rates are projected to increase by 5% in cities. Conversely, the estimated change in rural areas, where the majority of the poor is concentrated, is 40%.

Furthermore, I present evidence that there is wide variation in the vulnerability of different Mexican regions to projected climate change. While I find large increases in the annual mortality rate in both the Northeast and the Northwest (the hottest regions of the country), my model predicts a decline in the annual death rate of the South region.

Overall, my results suggest that by the end of the century, climate change will lead to a loss of more than 3.1 million life-years per annum (equivalent to one life-year lost every ten seconds.) This is an upper-bound estimate as agents are expected to adapt to a slowly warming climate.

Finally, in *Climate Shocks, Safety Nets, and Shielded Poor: Experimental Evidence from Rural Mexico*, I argue that extreme weather is a major source of vulnerability for rural poor households, not only because climate has a direct impact on agriculture but also because poor households usually are not equipped to deal with unexpected shocks. To cope with a crisis, poor households resort to strategies that simultaneously decrease their short-term welfare and make it harder for families to get out of poverty in the medium and long term.

With this essay, I show that in cases of market failure, government interventions are effective mechanisms to mitigate the negative impact of weather-induced income shocks. By combining experimental data for 24,000 households in 506 communities of rural Mexico for 1998 and 1999 with extreme-weather metrics that account for the non-linearity of climate impacts, I show that El Niño- and La Niña-related severe meteorological conditions lead to sharp declines in consumption and welfare outcomes, particularly among the poor, and more specifically on female-headed and indigenous households.

I examine the role of a poverty-alleviation program in Mexico by exploiting the fact that its rollout was phased, thus introducing random assignment that allows me to evaluate its impact on welfare. I show that the program shields its recipients by insulating them from weather-induced income shocks, allowing them to maintain stable consumption while reducing their propensity to resort to a variety of costly risk-coping strategies. The results are robust to several severe-climate-model specifications.

Overall, my estimates suggest that the provision of a safety net significantly raises expected utility by smoothing consumption and reducing inefficient behaviors *ex post*: the marginal gain in welfare from the provision of an income transfer can be almost three times as large as the increase in total consumption, depending on the households' level of risk aversion.

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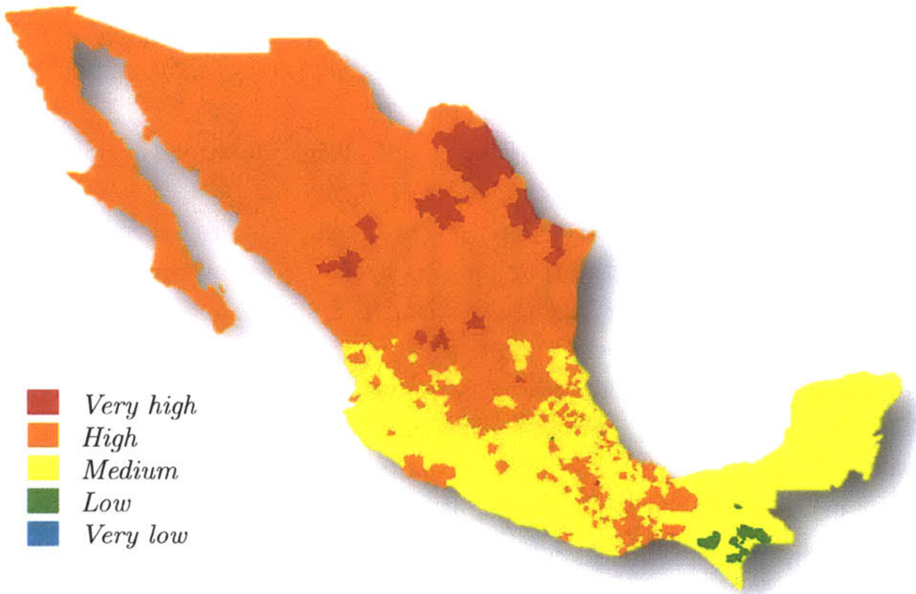

Figure 1. Vulnerability to high temperatures, by municipality
Source: Centro Nacional de Prevención de Desastres (2012)

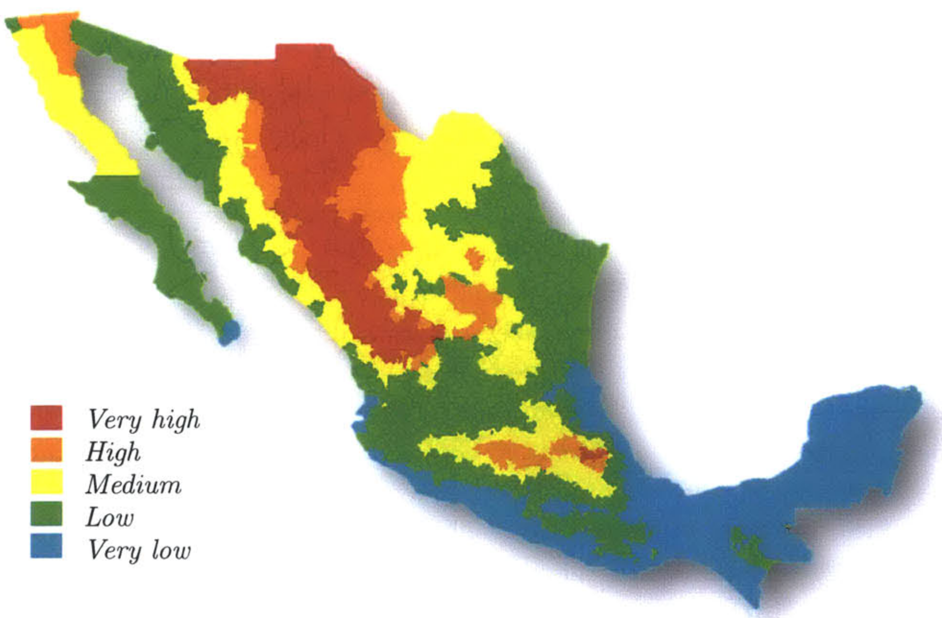

Figure 2. Vulnerability to low temperatures, by municipality
Source: Centro Nacional de Prevención de Desastres (2012)

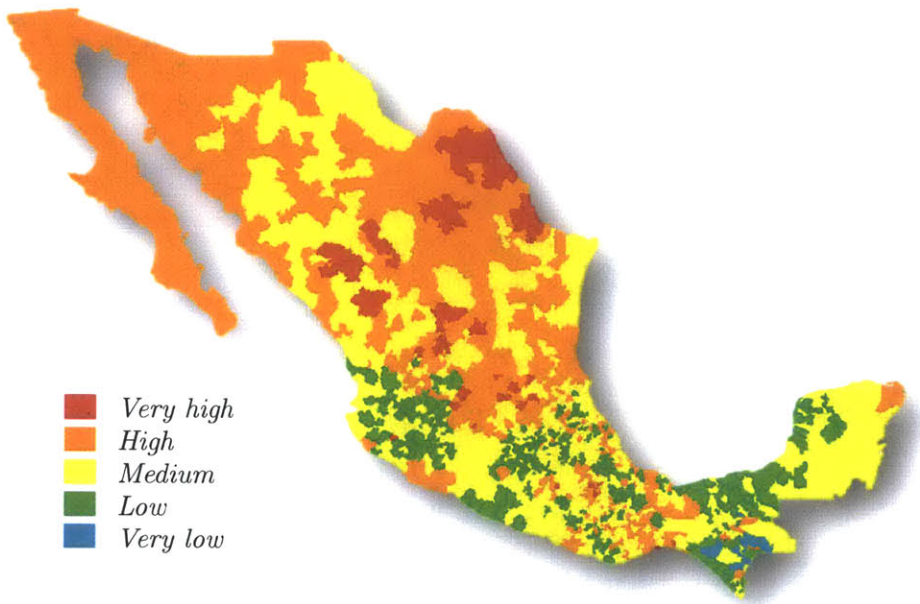

Figure 3. Vulnerability to low precipitation (drought), by municipality
Source: Centro Nacional de Prevención de Desastres (2012)

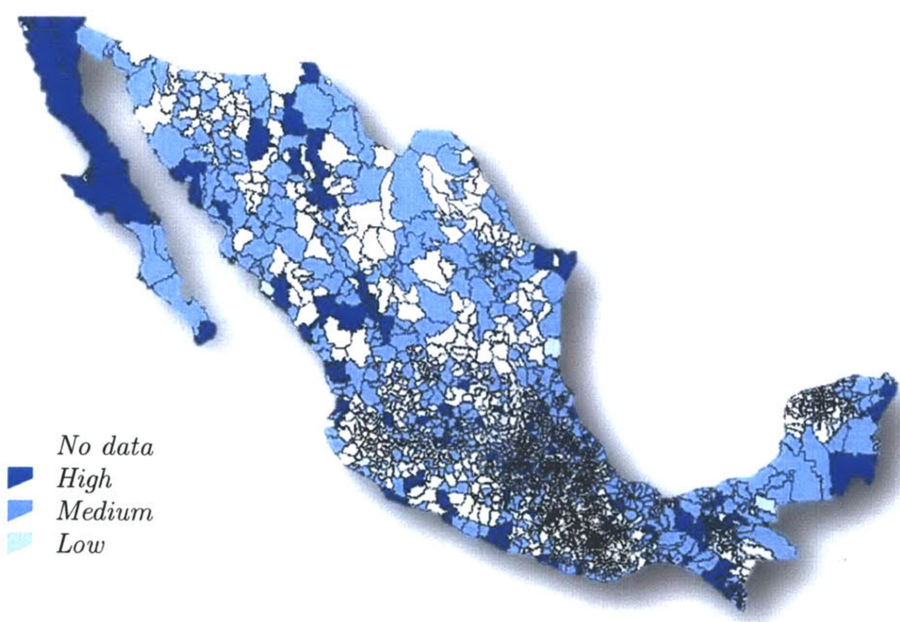

Figure 4. Vulnerability to high precipitation (floods), by municipality
Source: Centro Nacional de Prevención de Desastres (2012)

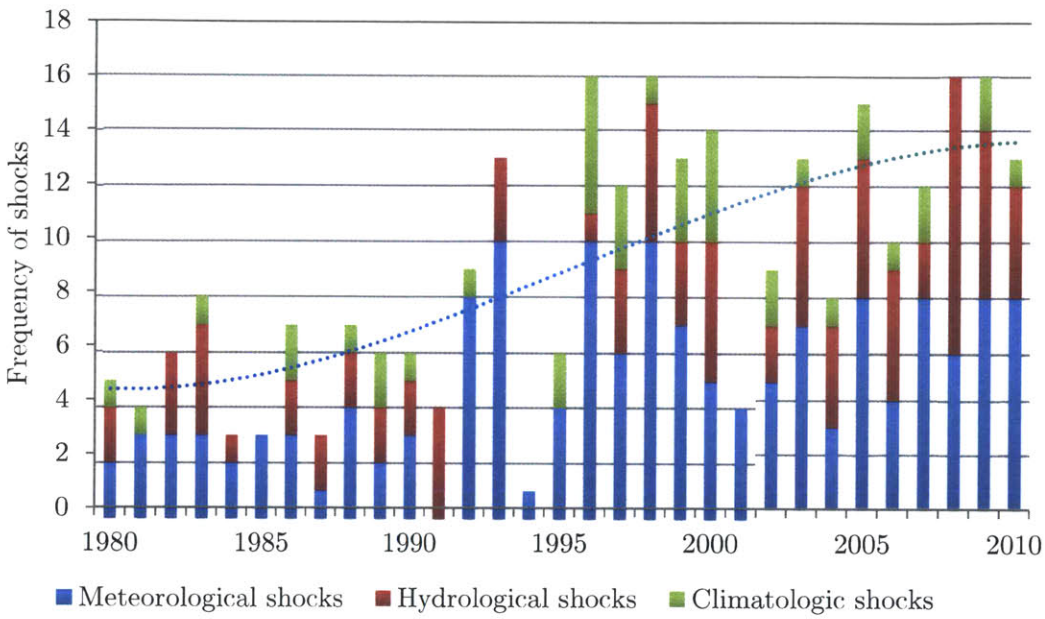

Figure 5. Major climate shocks in Mexico, by frequency and trend, 1980-2010

Source: Münchener Rückversicherungs-Gesellschaft, Geo Risks Research, NatCatSERVICE. *Note*: Meteorological shocks include storms only; hydrological shocks include floods and landslides; climatologic shocks include extreme temperatures, droughts and wildfires.

Chapter 1

The Welfare Impact of Extremes: Evidence from Random Fluctuations in Weather†

1 Introduction

The mechanisms through which weather impacts human welfare are complex and rarely linear. They often encompass a wide variety of factors ranging from geographical location, economic development, settlement patterns and behavioral adaptation to intra-seasonal acclimatization, demographic characteristics, urbanization, and environmental pollutants. Combined, these factors make some areas more vulnerable to climate variability than others (O'Brien & Leichenko 2000.) Mexico and other developing countries are a clear example. Inherent features of the developing world make people residing in industrializing regions more exposed to the negative impacts of weather than their developed-world counterparts. On average, people in developing countries spend more time outdoors (Basu & Samet 2002), whether at their workplace, producing goods for their household's own use and maintenance, commuting, or even carrying out activities to meet biological needs such as eating, sleeping, and relaxing. Even indoors, households in developing countries are more likely to lack air conditioning or display other features providing insulation from extreme weather (Rothman & Greenland 1998.)

† JEL classifications: I12, Q12, Q51, Q54. Keywords: weather shocks, climate extremes, mortality, agricultural income, Mexico. I am particularly grateful to Karen R. Polenske, Esther Duflo, Amy Glasmeier, Carlos Ludena, Dave Donaldson, Sebastián Miller, Leonardo Sánchez and my colleagues at the Inter-American Development Bank Dissertation Fellowship Program, Washington, D.C., and seminar participants at the Massachusetts Institute of Technology, Harvard University and Columbia University, as well as two anonymous referees for constructive comments. I thank MIT, CONACyT and IADB for the generous financial support provided for this chapter.

In developing-country settings specifically, the power of weather can be generally understood through two specific types of channels. One is direct: weather impacts human physiology through thermal stress and changes in metabolic rates, as well as increased incidence of diseases caused or spread by severe climatic conditions. The linkages between extreme climatological conditions as determinants of disease emergence are particularly significant in Mexico (see Figure 1). In an extreme situation, severe weather may ultimately lead to death. In fact, the effect of extreme weather on mortality is a public health threat of considerable magnitude: even though *economic* (including insured) disaster losses associated with climate and geophysical events are higher in developed countries, *fatality rates* are higher in developing countries. During the period from 1970 to 2008, over 95 percent of deaths from inclement weather occurred in developing countries (IPCC 2012.)

Substantial epidemiological evidence documents a strong relation between severe weather and mortality. The body adapts thermally to survive in drastic temperature environments, typically through thermoregulatory control mechanisms, such as shivering, arteriovenous shunt vasoconstriction, sweating and precapillary vasodilation in cold and hot environments, respectively. However, these physiological processes are only effective within certain limits. Weather can be so extreme that such adjustments fail to balance body and ambient temperature, which can lead to strokes, hypothermia and hyperthermia, and other conditions that may be fatal.

Many studies focusing on both industrial and developing countries have consistently shown that extreme heat is a natural hazard that can have a pronounced effect on human wellbeing. This relationship has been considered relevant to public health for millennia[6] and empirically researched as early as the 1930s: in a classic study, Gover (1938) reports excess deaths associated with elevated ambient temperature exposure in

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[6] Already in *Περί Αέρων, Υδάτων, Τόπων* (*On Airs, Waters, Places*), a fifth-century B.C. medical treatise ascribed to Hippocrates, the author deals with the effects of climate on health. The text starts by arguing that "whoever wishes to investigate medicine properly, should proceed thus: in the first place to consider the seasons of the year, and what effects each of them produces for they are not at all alike, but differ much from themselves in regard to their changes. Then the winds, the hot and the cold, especially such as are common to all countries, and then such as are peculiar to each locality." See **http://classics.mit.edu/Hippocrates/airwatpl.mb.txt** for the full-text translation.

86 U.S. cities from 1925 to 1937. Studies of army recruits published in the 1940s (Schickele 1947) and 1950s (Stallones, Gauld & Dodge 1957) also underscore an association between ambient heat exposure and death. More recently, Hajat, O'Connor, and Kosatsky (2010) observe that in Europe, increases in emergency hospital admissions among individuals with respiratory diseases have been noted during hot weather, while in studies from the United States, heat-related increases were noted in admissions for heart disease, acute myocardial infarction, and congestive heart failure. Using district-level data for India, Burgess et al. (2011) show that hot days and deficient rainfall cause large increases in mortality within a year of their occurrence in rural regions. Basu and Samet (2002) and Kovats and Hajat (2008) present a general review of the literature on the effects of hot temperature on mortality rates.

The evidence is also robust for cold climate. Deschênes and Moretti (2009) estimate that the aggregate effect of cold weather on mortality is quantitatively large, the number of annual deaths attributable to cold temperature being equivalent to 0.8 percent of total deaths in the United States. This effect is even larger in low-income areas. Hashizume et al. (2009) characterize the daily temperature-mortality relationship in rural Bangladesh and find that for the period between 1994 and 2002, a 1°C decrease in mean temperature was associated with a 3.2 percent (95 percent confidence interval: 0.9–5.5) increase in mortality, with deaths resulting from perinatal causes sharply increasing with low temperatures. In an international study of temperature and weather in urban areas using data from 12 cities in developing countries, including Mexico City and Monterrey, McMichael et al. (2008) find a *U*-shaped temperature-mortality relationship, with significant death rate increases at lower temperatures. Analitis et al. (2008) study the short-term effects of cold weather on mortality in 15 European cities and find that a 1°C decrease in temperature was associated with a 1.3 percent increase in the daily number of total natural deaths and increases of 1.2 percent, 1.7 percent and 3.3 percent in cerebrovascular, cardiovascular and respiratory deaths, respectively, the increase being greater for the older age groups. Hassi (2005) presents a review of the literature on cold exposure mortality.

The other mechanism through which weather impacts humans, especially in developing countries, is indirect. It can be understood as a "food-security mechanism," characterized in general terms by two different channels. The first channel could be described as an "income-based channel" in which health outcomes are negatively influenced as a result of adverse weather disrupting the household's sources of income on which it relies for subsistence (Burgess et al. 2011.) Indeed, many regions in the world, and particularly the poorest, rely almost solely on small-scale, climate-sensitive subsistence farming, which is especially susceptible to inclement weather (IPCC 2012.) Mexico is a good example. Although the agricultural sector does not have economic relevance (as a percentage of the country's gross domestic product), it is a socially critical sector, not only because agriculture is the source of livelihood of a major part of Mexico's population but also because rural poverty exacerbates climate-induced agricultural vulnerability (see Figures 2 and 3.)

The second channel could take the form of a "consumption-based channel" whereby consumption of basic goods and food intake is restrained as a result of natural-calamity-induced supply shortages, speculative behavior, and increased demand to deal with uncertainty. The economic consequence of extreme weather is higher food prices, which ultimately affect the poor as a result of reduced purchasing power, increasing their likelihood of becoming famine victims as a result (Lin & Yang 2000.) Overall, weather has played a major role in 17 out of 24 major famines from 1693 through 2005 (for a listing of famines, see Ó Gráda 2007, p. 20), suggesting that the food-security mechanism is as relevant as the direct human physiology channel.[7]

There are many instances in both the development and agricultural economics literatures exposing how the income-based channel operates in a self-sufficiency farming context. For instance, in an influential article, Sen (1981, p. 449) discusses the Ethiopian and Bangladeshi famines of the early 1970s and weather (droughts and floods, respectively), and points out that in both cases farmers were disproportionally affected: "the farming population faced starvation, because their own food output was insufficient, and they did not have the ability to buy food from others, as food output is also their source of income." Food output is also negatively impacted by extreme tempera-

[7] Intuitively, given that both channels of the food-security mechanism ultimately affect human health, it is also useful to consider both income and consumption-based channels as two specific mechanisms through which human physiology is impacted. In this sense, the physiological mechanism can be seen as the "aggregate effect" of weather on mortality.

ture, as shown by Hatfield et al. (2011.) Wheeler et al. (2000) find that crops are especially at risk when extreme temperatures take place near or during their pollination phase, while Prasad et al. (2006) document the adverse impact of extreme temperatures on crop yields. In addition, Porter and Semenov (2005) and Hurkman et al. (2009) have found that even if inclement climate does not lead to harvest loss, weather extremes do affect photosynthesis and respiration rates, among other crop development and growth processes, causing lower crop quality and micronutrient malnutrition. Kettlewell, Sothern, and Koukkari (1999), Gooding et al. (2003), and Martre et al. (2003) show that there is a significant negative association between extreme weather and both protein content and nutritional properties.

The role of weather in the consumption-based channel is also studied by many analysts. In the same study on famines presented above, Sen (1981) discusses that the wages paid to farm laborers in 1942 did not keep up with the rising price of food, which was caused, *inter alia*, by a hurricane that affected rice harvests, as well as inflation in Calcutta, triggered by the Raj putting money into war production. This resulted in farmers suffering a reduction in their ability to command power over food, which eventually resulted in the Bengal famine of 1943. Similar cases in Africa and Europe are discussed at length by Drèze and Sen (1989) and Ó Gráda (2007.) In a recent report, the staff of the Food and Agriculture Organization of the United Nations (FAO 2008) examines the multiple weather hazards that potentially affect food supply chains when agricultural production is not consumed where it is produced: transporting food is contingent upon transport, storage, and distribution infrastructure that is vulnerable to the destructive nature of severe weather. The more extreme climate events are, the more pronounced the damage to that infrastructure, which is likely to result in disrupted processing and delivery chains. This is reflected in higher food prices, acutely impacting the poorest households, who spend a large share of their income on food (IPCC 2012.)

In the next section, I show both the direct and the indirect channels through a theoretical model.

2 A Theoretical Framework of Extreme Weather

A theoretical model that portrays the relationship between extreme weather and mortality or other health outcomes should include the direct and indirect mechanisms through which weather impacts human life. A starting point for this purpose is an extension of the health as human capital developed by Becker (2007) and adjusted by Burgess et al. (2011) to incorporate choices that increase agents' probability of survival under extreme heat. I expand it further in order to account for the negative effects of extreme cold weather.

Consider the following utility function specified with a constant discount factor for different time periods for an infinitely lived agent:

$$V = \mathbb{E}\left[\sum_{t=0}^{\infty} D^t S_t u_t(c_t)\right] \tag{1}$$

where u_t is the utility at period t that depends on consumption during the same period, c_t. D is the discount factor and S_t is the probability of the agent being alive (i.e., $1 - S_t$ is the probability of death) during period t, which equals the product of the conditional probabilities of being alive given that the agent was alive during the previous period:

$$S_t = s_0 s_1 s_2 \ldots s_{t-1} = \prod_{t=0}^{t-1} s_t \tag{2}$$

Suppose now that the probability of survival in period t is a function of nutrition, N, which is under the agent's control, subject to a budget constraint, and weather, W, which is assumed to be exogenous. For the purposes of this paper, I define nutrition as caloric intake and weather as the number of days throughout the period with inclement (i.e., excessively cold or excessively hot) climate. Hence, let $s_t = (N_t, W_t)$ and assume that such a function is increasing in N, but decreasing in W. We thus have two types of consumption goods: food, denoted by N, and a composite good, G, whose consumption is directly valued by the agent.

In this specification, extreme weather, *ceteris paribus*, has a direct impact on the probability of the agent's survival, which I defined as the *direct* impact of weather on human physiology in the previous section. Likewise, the assumption that s is increasing in N is what I previously identified as the food-security mechanism, which impacts human wellbeing *indirectly* through disruptions in the income stream or subsistence consumption that lead to severe reductions in caloric intake.

In this formulation, I follow the event-timing specification of Burgess et al. (2011): given weather conditions for period t, the agent chooses her bundle of goods $(N_t(W_t), G_t(W_t))$. Then the agent's death shock takes place, with the probability of surviving death $s_t = (N_t, W_t)$. If the agent does survive through the next period, the function V gives her intra-period utility.

For simplicity, I assume that the budget constraint has a constant interest rate, and perfect and fair annuity and capital markets. Likewise, I assume that the price of food is p^N, while that of the composite good equals p^G, with both being constant over time. Notice that if expenditures in a given period surpass income, future savings will have to pay off the due balance. Thus

$$s_T(y - p^N N_T - p^G G_T) = \mathbb{E}\left[\sum_{t=1}^{\infty} \frac{S_t(p^N N_T + p^G G_T - y)}{(1+r)^t}\right] \tag{3}$$

If the agent maximizes her utility function (1) in period 0 subject to the budget constraint (3), we arrive at the optimal intertemporal consumption choice

$$\frac{u'(c_0)\mathbb{E}[s_1]}{D\mathbb{E}[s_1 u'(c_1)]} = 1 + r \tag{4}$$

whereby the first-order condition for the choice of caloric intake is

$$\frac{\partial s_0}{\partial N}\left(u(c_0)+\mathbb{E}\left[\sum_{t=1}^{\infty}D^t S_t u_t(c_t)\right]\right)=\frac{\partial s_0}{\partial N}\mathbb{E}[V_0]=\lambda p^N s_0 \tag{5}$$

This is an intertemporal characterization of optimal food choice whereby the marginal benefit of spending on food at time t equals the marginal cost of spending on food at time t. Equation (5) implies that the optimizing agent equalizes the present-value marginal flow benefit from the control across periods.

This first-order condition can be used to determine the extent to which the agent would be willing to pay to insulate herself from inclement weather in period 0. Burgess et al. (2011) characterize a transfer τ^* that is a function of weather, W, in period 0. Such a transfer holds expected lifetime utility V constant regardless of the value of W, so that

$$\frac{d\tau*(W_0)}{dW_0}=-\frac{dy(W_0)}{dW_0}+\frac{\partial N_0}{\partial W_0}-\frac{ds(N_0,W_0)}{dW_0}\mathbb{E}\left[\frac{V_0}{s_0\lambda}\right] \tag{6}$$

The amount the agent would be willing to pay to insulate herself from inclement weather in period 0 depends on three conditions. First, the willingness to avoid the risk of being exposed to the negative physiological impacts of weather, which as discussed in the previous section, may ultimately lead to death. This is represented by the third term in equation (6), $-\frac{ds(N_0,W_0)}{dW_0}\mathbb{E}\left[\frac{V_0}{s_0\lambda}\right]$, which is the product of the probability of surviving given weather conditions W, $\frac{ds(N_0,W_0)}{dW_0}$, and which Becker (2007, p. 384) refers to as "the statistical value of life," which is the monetary value given by the agent of surviving through period 0, $\mathbb{E}\left[\frac{V_0}{s_0\lambda}\right]$.

Second, given that extreme weather puts food-security at risk, the agent would be willing to pay an amount equal to the first term of equation (6), $-\frac{dy(W_0)}{dW_0}$, to avoid any loss of income resulting from extreme weather. Third, the agent would need to be compensated for any changes in terms of food expenditure derived from the agent trying to reduce her chance of dying by counterweighing the negative effects of severe climate through the acquisition of more nutrients. This is expressed by the second term of equation (6), $\frac{\partial N_0}{\partial W_0}$.

Based on equation (6), I propose an empirical approach that estimates the effect of weather on human physiology, particularly on death, as well as that of climate on variables that determine incomes. As a result of money fungibility, it does not matter whether the agent faces a climate shock through either the human physiology or the food-security channel. The agent is only concerned about being insulated from inclement weather, for which she is willing to pay a price. A consideration that needs to be emphasized is that, given that markets are complete in this model, a policy that corrects market failure is irrelevant. However, as Burgess et al. (2011, p. 10) argue, such a model "does characterize the value that households place on avoiding temperature extremes, which an external funder, such as a foreign donor, might wish to use to compare the merits of competing policy proposals."

In the next section, I discuss the data I use to carry out an empirical analysis based on this theoretical framework.

3 Data

As I have argued throughout this paper so far, weather impacts humans via two channels, one that is direct, resulting from severe climate affecting human physiology, and another that is indirect, whereby weather disturbs the mechanisms through which households secure their food consumption. The extreme consequence of both channels is death.

An empirical specification of the theoretical framework presented above, which illustrates the human impact of weather, requires data on three types of variables: one that portrays human physiology, one that portrays food security, and one that portrays climate.

Typical variables that may work well to assess the impact of weather variation on human physiology include the incidence of particular water and vector-borne diseases, hospital admissions, clinic attendance, morbidity rates, and mortality rates (WHO, WMO & UNEP 2003.) In terms of variables that are likely to reflect a given community's degree of food security—especially in low and middle-income area contexts—income, job productivity and nature of job, crop production, and food consumption are all plausible proxies (USAID 1992.) Finally, the natural choices for studying climatic phenomena are temperature, pressure, rainfall, hail, aridity, wind, as well as the occurrence of certain weather events like tornados and cyclones (WMO 2012.)

As good evidence requires good data, I selected those variables generated with high frequency, high spatial disaggregation, and high-quality monitoring. The following constitute the variables that I employ for the following empirical analysis.

3.1 Mortality

To calculate mortality rates, information on deaths, births, and population is needed. I obtain death and birth counts data at the municipal level through each state's Civil Registry Office. Because each state has its own registration data and formats, I digitize and harmonize the 32 datasets (31 state datasets and one dataset for Mexico City) using standardized codes for births, deaths, and fetal deaths. I collect monthly data for the period January 1990-December 2010 for 2,454 Mexican municipalities (99.9 percent of the total.)

Given that annual population data are not available for Mexican municipalities, I construct a population monthly time series using censal information for population in combination with migration flow data obtained from Mexico's National Council of Population Demographic Indicators and the State and Municipal Database System of Mexico's National Institute of Statistics (INEGI.) These data are available for years 1990, 1995, 2000, and 2010. For intercensal years, I estimate (midyear) population using the component method, which is defined by the use of estimates or projections of births, deaths, and net migration to update a population (Hollmann, Mulder & Kallan 2000.) In its simplest statement, the component method is expressed by the following equation:

$$P_t = P_{t-1} + B_{t-1,t} - D_{t-1,t} + M_{t-1,t} \tag{7}$$

where P_t = population at time t;

P_{t-1} = population at time $t - 1$;

$B_{t-1,t}$ = births, in the interval from time $t - 1$ to time t;

$D_{t-1,t}$ = deaths, in the interval from time $t - 1$ to time t; and

$M_{t-1,t}$ = net migration, in the interval from time $t - 1$ to time t.

For simplicity, I compute intercensal net migration using what demographers refer to as the Das Gupta method (Das Gupta 1991.) This technique assumes that the ratio of the intercensal estimate to the postcensal estimate should follow a geometric progression over the five-year period. Naturally, there is no universal norm for producing intercensal migration estimates, and I could employ other methodologies.

With these variables, I construct a crude (total) mortality rate, which I define as the total number of deaths (excluding fetal deaths) per period per 1,000 people (see Figure 4). In addition to the crude mortality rate, I also distinguish among two subtypes of mortality indicators: infant mortality rate (i.e., the number of deaths of children less than 1 year old per period per 1,000 live births) and perinatal mortality rate (i.e., the number of stillbirths per period per 1,000 live births) (see Figures 5 and 6.) I also compare these mortality rates by area, defining the rural mortality rate as the mortality rate in communities with fewer than 2,500 residents (Figure 7), and urban mortality rate as the mortality rate in communities with 2,500 residents or more (Figure 8.) Table 1 presents relevant descriptive statistics.

The comparative analysis of urban and rural areas is of particular relevance. The distinction follows an intuitive logic: the food-security mechanism is more likely to find empirical support in rural communities. The reason is twofold: on the one hand, extreme weather has a clear and direct impact on agriculture, and this sector is the main source of employment for rural regions. Figures 9 and 10 illustrate a clear spatial overlap between rurality and agricultural specialization. The latest Household Income and

Expenditures National Survey (INEGI 2011) is also indicative of this phenomenon: in 2010, almost 62 percent of surveyed households living in rural communities worked in the agricultural sector, while only 7 percent of households residing in urban areas did. On the other hand, this spatial imbalance translates into significant differences in income: the same survey reports that, also in 2010, households where no members were employed in agriculture had an income, on average, of 13,365 Mexican pesos per month (1,062 USD.[8]) Households with some (but not all) members being employed in the primary sector of the economy earned, on average, 8,618 pesos (686 USD.) Finally, in the case where the entire household is engaged in agricultural work, monthly income averages 4,841 pesos (385 USD), or roughly a third of income in non-agricultural households.

These differences are reflected in two different patterns of household consumption: monthly expenditures in urban areas are high (relative to rural communities) and food consumption has a relatively smaller share of total expenditures. Urban households spend on average 8,878 pesos (707 USD) per month, of which almost 32 percent is spent on food. In contrast, rural households spend on average 4,602 (366 USD) pesos per month, of which 40 percent is spent on food. Table 2 summarizes these discrepancies.

3.2 Agricultural Outcomes

I obtain data for agricultural outcomes for the period 1994-2009 using Mexico's Agro-alimentary and Fishing Information System. I obtain information on the value of agricultural output (in thousands of pesos), and total hectares under crop cultivation (planted and harvested) at the municipal level for 2,454 municipalities.

In addition to totals, I collect municipal data for 10 major crops[9] for the volume of production (in tons) and average prices per ton. Using this dataset, I create two additional indicators: I define agricultural productivity as the value of agricultural output

[8] Based on the average midpoint exchange rate of 0.0796 MXN/USD from August 21, 2010 through November 28, 2010, the period when the survey was carried out.

[9] These crops are green alfalfa, beans, corn, green chili, oats, pastures, sorghum, tomato, tomatillo, and wheat.

divided by harvested hectare, whereas crop yields are expressed as the volume of production divided by harvested hectare. Monetary values were expressed in Mexican pesos of 2009. I deflated prices using a price index that weights the municipal price of each of the 10 major crops by the value of agricultural output of that crop in a given year.

Given the nature of the agricultural cycle in Mexico, the calendar year and the agricultural year differ. By convention, the agricultural year in Mexico lasts 18 months: it begins on October 1 of year $t - 1$ and ends on March 30 of year $t + 1$, and thus the first three months of a given agricultural year overlap with the last three months of the previous agricultural year. I collect annual agricultural data based on agricultural years. In my empirical analysis, I reconcile calendar years and agricultural cycles by synchronizing weather data accordingly. In addition, my analysis of the agricultural data shows that, even though there are differences resulting from geographical location, elevation, rainfall, coastal proximity, and varying photoperiods, the period when crop growing intensifies starts typically in early April and ends in late August. For my empirical analysis, I thus define this period as Mexico's growing season. Similarly, the period of November through February is characterized by crop-growing inactivity, and throughout this paper I will refer to this timespan as the non-growing season. Table 3 presents summary statistics for several agricultural outcomes, including yields and volume of production for corn, Mexico's main staple.

3.3 Weather

The most essential data to carry out any empirical analysis on weather and its impacts are, of necessity, climatic records. A variety of models provide environmental analysts with climatic observations, and I employ some to assess weather impacts in Mexico in terms of human, environmental, and agricultural outcomes. In studying the impact of severe weather on health and cognitive development, Aguilar and Vicarelli (2011) use precipitation data at 0.5 degree resolution climate grids, which were generated by the Climate Research Unit and the Tyndall Centre for Climate Change Research, both at the University of East Anglia. Sáenz Romero et al. (2010) develop spatial climate models to estimate plant-climate relationships using thin-plate-smoothing splines of ANUSPLIN software, created by the Australian National University. Pollak and Corbett (1993) use spatial agroclimatic data to determine corn ecologies.

The underlying problem with these and other works that follow similar methodologies is their use of monthly climatic data. Using monthly climatic data is problematic due to the nonlinear effects of weather, which may be concealed when, for example, daily observations are averaged into monthly or seasonal variables. In effect, daily and even finer-scale weather data facilitate estimation of models that aim to identify nonlinearities and breakpoints in the effect of weather. Schlenker and Roberts (2009) use daily temperature data and find a nonlinear asymmetric relationship between weather and crops yields in the United States, with yields decreasing more rapidly above the optimal temperature vis-à-vis their increasing below the optimal temperature. The assumption of nonlinearity is particularly critical for studies like this one, where I attempt to represent the relationship between weather and human physiology. In many studies, for the case of mortality, researchers have found a *J*- or *U*-shaped curve appropriate to describe the association, with elevated mortality being observed at temperature extremes and relatively lower mortality at moderate temperatures (Burgess et al. 2011; Curriero et al. 2002; Deschênes & Greenstone 2011; Huynen et al. 2001; Kunst, Looman & Mackenbach 1993.)

I use daily temperature and precipitation data from the North American Regional Reanalysis (NARR) model (NOAA, 2012.) The NARR project is a long-term, high-frequency, dynamically consistent meteorological and land-surface-hydrology dataset developed by the National Centers for Environmental Prediction (NCEP) as an extension of the NCEP Global Reanalysis, which is run over the North American Region. It covers the period 1979 to 2010 and data are available at three-hour intervals (i.e., eight data points per day), on a Northern Hemisphere Lambert Conformal Conic grid with a resolution of 0.3 degrees (32km)/45 layers at the lowest latitude. In addition to the modeling benefits of high spatial resolution, I employ NARR due to the model's good representation of extreme weather events, resulting from the model outputting all "native" (Eta) grid time-integrated quantities of water budget. In a recent study, Mesinger et al. (2006) compare the NARR precipitation for January 1998 (when the El Niño effect was underway) with observed precipitation. Their comparison shows that over land there is an extremely high agreement between NARR and observed precipitation, even over the complex western topography of Mexico.

Other variables could be employed for future work. The NARR dataset also includes information on wind speed, humidity, elevation, and other common climatic factors, but evidence shows that, for the most important crops of Mexico in terms of output (i.e., corn, sorghum, and wheat), temperature and precipitation are the two weather elements that can effectively inhibit plant growth and development to the point of crop failure (Ministry of Agriculture of Mexico 2012b.) Conversely, non-optimal values in altitude, soil quality, or light-intensity requirements may only retard growth or reduce yields, but these factors are not likely to put crops at imminent risk (FAO 2007.)

I construct daily temperature and precipitation data in two simple steps. First, I apply a spherical interpolation routine to the data: I take weighted averages of the daily mean temperature and accumulated precipitation of every NARR gridpoint within 30 kilometers of each municipality's geographic center, with the inverse squared haversine distance between the NARR gridpoint and the municipality centroid as the weighting factor.[10] Second, I distribute all the (365, or 366 for leap years) daily temperature estimates in a given year over 14 ranges: daily mean temperature lower than 10°C; daily mean temperature higher than 30°C, and 10 two-degree-wide intervals (i.e., 10°C-12°C, 12°C-14°C,..., 28°C-30°C) in between. Similarly, I distribute the daily accumulated rainfall estimates over 15 two-millimeter-wide ranges (i.e., 0-2mm, 2-4mm,..., 28-30mm) plus an extra range for daily accumulated precipitation exceeding 30mm, and another range containing exclusively days without rainfall. Slicing the weather data into small intervals is important for the empirical strategy that will follow, for it maintains weather variation in any given specification, thus accounting for the nonlinear effects of weather extremes discussed above.

[10] The haversine distance measure is useful when the units are located on the surface of the earth and the coordinate variables represent the geographical coordinates of the spatial units and a spherical distance between the spatial units needs to be calculated. This is accomplished by calculating $d_{st} = r \times c$, where r is the mean radius of the Earth (6,371.009 kms); $c = 2\arcsin(\min(1, \sqrt{a}))$; $a = \sin^2\phi + \cos(\phi_1)\cos(\phi_2)\sin^2\lambda$; $\phi = \frac{1}{2}(\phi_2 - \phi_1) = \frac{1}{2}(x_2[t] - x_2[s])$; $\lambda = \frac{1}{2}(\lambda_2 - \lambda_1) = \frac{1}{2}(x_1[t] - x_1[s])$; $x_1[s]$ and $x_1[t]$ are the longitudes of point s and point t, respectively; and $x_2[s]$ and $x_2[t]$ are the latitudes of point s and point t, respectively.

Figures 11 and 12 illustrate these ranges for the period 1979-2009. The height of the bars represents the weighted average number of days across municipality-by-year temperature and rainfall realizations, where the municipality-by-year's total population is the weight. The weighted average temperature is 18.6°C, while the weighted average daily accumulated precipitation is approximately 2mm.

An alternative approach to using ranges is suggested by Burgess et al. (2011.) They construct a measure of the cumulative number of degrees-times-days that exceed 32°C in a year, in an attempt to reflect the nonlinear effects of temperature.[11] Although it collapses daily weather observations into a single metric, this measure, by taking into account the number of degrees per day above a certain threshold, still indirectly accounts for the nonlinear effects of weather. For this paper, I follow a similar strategy by constructing four aggregate measures: (1) the cumulative degrees-times-days that exceed 30°C in a year, (2) the cumulative degrees-times-days below 10°C in a year, (3) the total millimeters-times-days that exceed 8 millimeters, and (4) the total millimeters-times-days below 3 millimeters. The rationale behind these thresholds is ecological. These are the minimum and maximum temperature and precipitation requirements for corn, Mexico's staple crop. Beyond these values, corn usually begins to stress, putting at serious risk its survival (Gómez Rojas & Esquivel Mota 2002; Ministry of Agriculture of Mexico 2012a; Neild & Newman 1990; North Dakota Corn Utilization Council 1997.)

Table 4 summarizes the descriptive statistics for the temperature and precipitation variables employed.

4 Empirical Strategy

I use two empirical specifications to establish the relationship between weather and mortality. The first one is an attempt to capture the full distribution of annual fluctuations in weather and is based on equation (8):

[11] The choice of using 32°C as the threshold is based on the public health and agronomy research that has consistently shown that temperatures higher than 32°C are severe for both human and crop physiology (Burgess et al. 2011.)

$$Y_{mt} = \sum_{j=1}^{12} \theta_j temp_{mtj} + \sum_{k=1}^{17} \rho_k rain_{mtk} + \alpha_m + \gamma_t + \lambda_r^1 t + \lambda_r^2 t^2 + \varepsilon_{mt} \tag{8}$$

where Y_{mt} is the log (crude or an alternative) mortality rate (or agricultural outcome of interest) in municipality m in year t (using levels virtually leaves the results unchanged, but for the sake of clarity, I use logs.) $temp_{mtj}$ and $rain_{mtk}$ are the separate j temperature and k precipitation ranges described above for municipality m in year t.

The impact of temperature thus equals the sum of all j ranges, whereas the impact of precipitation is equivalent to the sum of all k ranges. Notice that the only functional form restrictions in this specification are (1) that the mortality impacts of temperature and precipitation are constant within each 2-degree and 2-millimeter range, respectively, and (2) that all days with temperatures/rainfall above (below or equal to) 30°C/30mm (10°C/0mm) have the same impact in terms of mortality.

α_m is the fixed effect of municipality m. I include municipality fixed effects to control for the average differences across municipalities in any observable or unobservable predictors of log mortality rate so that, for instance, demographic, socioeconomic, or clinical impacts will not be confounded with that of weather. Similarly, γ_t is the unrestricted time-fixed effect of year t. These fixed effects control for time-varying differences in the dependent variable that are common across municipalities, such as the introduction of the Seguro Popular in 2003. Because such shocks are unlikely to have the same effect at the regional level (for instance, among Seguro Popular delegations, the pricing of prescription drugs varies greatly across regions), equation (8) also includes quadratic polynomial time trends λ_r for the r=5 mesoregions of Mexico (Northeast, Northwest, South, Center, and Center-West) which, at least in terms of weather, are fairly homogenous. Finally, ε_{mt} is the stochastic error term.

The second specification fits equation (9):

$$\begin{aligned} Y_{mt} = {} & \beta CDD30_{mt} + \delta CDD10_{mt} + \varphi CMMD8_{mt} + \eta CMMD3_{mt} + \\ & \alpha_m + \gamma_t + \lambda_r^1 t + \lambda_r^2 t^2 + \varepsilon_{mt} \end{aligned} \tag{9}$$

where $CDD30_{mt}$ ($CDD10_{mt}$) is the cumulative degrees-times-days that exceed 30°C (below 10°C) in municipality m in year t. Similarly, $CMMD8_{mt}$ ($CMMD3_{mt}$) is the cumulative millimeters-times-days that exceed 8mm (below 3mm) in municipality m in year t. This specification also includes municipal fixed effects α_m, time fixed effects γ_t, quadratic polynomial time trends λ_r, and a stochastic error term ε_{mt}.

By definition, equation (9) is a more restrictive approach than equation (8), given that it assumes that the impact of weather on mortality is determined by extreme temperatures and rainfall only. However, with only four estimated coefficients instead of 29, sensitivity of the results is gained due to improved statistical power to detect weather effects.

As discussed by Burgess et al. (2011) and Deschênes and Greenstone (2011), the validity of my empirical strategy for studying the weather-mortality relationship relies on the assumption that equations (8) and (9) yield unbiased estimates of the $\theta_j, \rho_k, \beta, \delta, \varphi$, and η vectors. Given the two-way fixed-effect identification strategy employed, any omitted variables that are constant over time and/or particular to one municipality will not bias the estimates, even if the omitted variables are correlated with the explanatory variables. If weather variability is supposed to be random, then it is plausible to assume that it is uncorrelated to unobserved mortality determinants.

5 Results

I present two different sets of results, based on the two hypothesized mechanisms through which extreme weather affects humans to the point of causing death: (1) the human physiology channel (severe weather impacts human physiology through thermal stress and disease, which in an extreme situation may lead to death) and (2) the food-security channel (mortality rates are driven as a result of adverse weather disrupting either the household's sources of income on which it relies for subsistence or its purchasing-power capacity, or both, increasing the likelihood of becoming famine victims as a result.)

These results are derived from the fitting of equation (8), distributing temperatures and precipitation estimates over small intervals to maintain weather variation. Because observing a common variance structure over time is unlikely, my results are based on a cluster-correlated Huber-White covariance matrix estimator, which avoids the assumption of homoskedasticity (Wooldridge 2004.) In addition, I weight my empirical specification by the square root of the total municipal population, in an effort to correct for heteroskedasticity associated with municipal differences in estimation precision of mortality rates, having the additional advantage of presenting impacts on one person, rather than one municipality (Deschênes and Greenstone 2011.) Although temperature and precipitation are modeled in the same way, I only report temperature estimates. The findings show that precipitation, in general, is unlikely to have a significant independent influence on mortality and agricultural outcomes.

5.1 The Physiology Channel

Figure 13 presents the results of the impact of temperature on mortality rates. More specifically, it shows the estimated impact of an additional day in 12 temperature ranges, relative to a reference range, which in this case is the 16°-18°C.

Two patterns emerge. First, graphically, a *J*-shaped curve is fairly appropriate to describe the weather-death association. As theory predicts, moderate temperature ranges do not seem to have an impact on mortality rates. In fact, among the eight ranges that account for temperatures between 12°-26°C, only two are statistically significant at the conventional levels. Colder ranges, in general, do not have an effect statistically different from the reference range. Second, extreme hot weather does seem to have a sustained impact on death. All three ranges including the hotter temperature ranges are statistically different from the reference category. For instance, *one additional day* with an average temperature above 26°C increases mortality rates by at least 0.1 percent relative to a day with a mean temperature in the 16°C-18°C range.[12]

[12] Precipitation impacts are typically insignificant at the conventional levels, with the exception of the extreme-precipitation ranges (i.e., the far-left and far-right categories including days with no precipitation and rainfall exceeding 30mm., respectively) Although what can be thought of as the "drought range" (i.e., the range that includes days with no precipitation) does not comparatively have an important impact on death, extreme rainfall does pose significant threats to human wellbeing. One single day with rainfall higher than 30mm increases mortality rates by 0.7 percent relative to one with rainfall ranging from 6-8mm.

As I pointed out before, some studies have investigated the impact of extreme weather on perinatal and infant mortality. Hashizume et al. (2009) find that perinatal mortality sharply increases with low temperatures. Dadvand et al. (2011) conclude that extreme heat was associated with a reduction in the average gestational age of children, which is associated with perinatal mortality and morbidity. Burgess et al. (2011) show that weather extremes appear to increase infant mortality in rural India, but not in urban areas. Scheers-Masters, Schootman, and Thach (2004) find no evidence that elevated environmental temperatures have a significant role in the development of sudden infant death syndrome.

Figure 14 shows that there is no clear relationship between temperature, either extreme or moderate, and fetal mortality. If anything, colder temperatures seem to be associated with *lower* fetal mortality rates, but the effect is minimal. All the temperature ranges above 12°C are small in magnitude and insignificant. As for infant mortality, Figure 15 shows that extreme heat is positively associated with infant mortality rates, but in terms of extreme cold, it is not possible to reject the null hypothesis of equality with the base category. I note that the point estimate of days with temperatures higher than 30°C relative to the reference 16°-18°C range is 0.15 percent for the crude mortality response function, while it is 50 percent larger (0.23 percent) for the infant mortality specification. This finding echoes Deschênes and Greenstone's (2011) result that the impact on annual mortality of hot weather (i.e., higher than 90°F) for infants is twice as large as the point estimate for the general population. The impact of precipitation on both fetal and infant mortality is, with frequency, statistically nil.

Figures 16 and 17 show the relationship between weather and death by type of area. I analyze two types of areas: rural and urban. Recall that I define rural mortality rate as the mortality rate in communities with fewer than 2,500 residents, and urban mortality rate as the mortality rate in communities with 2,500 residents or more. It is important to emphasize that this differentiation is relevant because it would indicate that people living in rural areas are potentially more exposed to the negative impacts of weather, given that their main economic activity, agriculture, is easily upended by climate shocks.

From the analysis of these plots, several interesting findings emerge. In terms of temperature, the effect on death is virtually zero for urban areas: only two out of the 12 temperature ranges are significant, but small in magnitude, with no temperature ranges being associated with increases in mortality rates greater than 0.1 percent. Conversely, the response function between log rural mortality rate and temperature indicates that rural areas are especially vulnerable to the negative effects of extreme (particularly hot) temperatures. Although the variance of rural mortality is high (see Table 1), which results in wider confidence intervals, the five hottest temperature ranges (i.e., temperatures higher than 26°C) are all statistically significant and of higher magnitude than the urban coefficients. For example, exchanging a single day in the 16°C-18°C range for one in the >30°C range would lead to an increase in annual mortality rates of 0.2 percent in rural areas (for urban areas the coefficient is not statistically different from the reference range.) In terms of the precipitation response functions, for most coefficients, both for urban and rural areas, it is not possible to reject the null hypothesis of equality with the base range.

To evaluate the robustness of these results, I present in Table 5 several versions of equation (9) which, in spite of being less flexible than previous specifications of equation (8), offers sensitivity gains due to improved statistical power to detect weather effects. Column (1) shows the relationship between extreme weather and annual mortality. Once again, cold temperatures do not seem to have an effect on crude mortality rates. The impact of hot weather is, in comparison, as found before, considerable: each additional degree above 30°C per year is associated with a 0.02 percent increase in the crude mortality rate. In other words, a one-standard deviation (34.3 percent) increase in the cumulative-degree-days above 30°C would lead to a 0.7 percent increase in the crude mortality rates. Exposure to extreme precipitation patterns, defined as the cumulative-millimeter-days above 8mm or below 3mm, is positively associated with crude mortality rates. Each additional millimeter above or below the threshold causes a 0.01-0.02 percent increase in the crude mortality rate.

Columns (2) and (3) show the relationship between extreme weather and infant and fetal mortality rates. As with the previous specification, severe weather events do not seem to lead to an increase in mortality in infants or stillbirths, with the exception of extreme heat, which is associated with a 0.04 percent increase in infant mortality rates. Extreme precipitation patterns seem to be *negatively associated* with these types of mortality indicators, or at most, have a negligible positive effect.

In columns (5) and (6), I compare the effect of weather on mortality by type of area. Once again, the impact of cold weather is statistically zero. In terms of extreme heat and precipitation, I again find that rural areas are more vulnerable than urban areas. According to equation (9), the effect of an additional degree above 30°C per year on mortality rates is twice as large for rural regions relative to urban areas. In terms of precipitation, differences are more prominent, with exposure to an additional millimeter-day above 8mm having an impact on rural mortality rates approximately eight times larger than on urban mortality rates.

So far, I have shown that hot temperatures are associated with higher mortality rates. In particular, infants seem to be a segment of the population particularly vulnerable to extreme heat. The impact of cold temperatures is normally trivial. In addition, the impact of (hot) temperature seems to be differentiated: it is larger for rural regions than for urban areas. As for rainfall, the effect is ambiguous: depending on the specification, precipitation extremes may be strongly associated with higher mortality or reflect habitually insignificant estimates.

The rural/urban differentiation is to be expected if the food-security mechanism is at work. In particular, the "income-based channel," where health outcomes are negatively influenced as a result of adverse weather disrupting the household's sources of income on which it relies for subsistence is more likely to operate in rural regions. Agriculture, which is the economic sector most susceptible to weather variability, is the main income-generating activity in rural communities, while in urban centers industry and services play a more significant role (see Table 2.)

I test this hypothesis below, first by comparing the impact of weather during the growing season vis-à-vis the non-growing season. If weather leads to contractions in agricultural output, which in turn decreases income, constraining consumption and ultimately causing death, then extreme weather taking place during the growing season should be particularly damaging, but severe weather events occurring in the non-growing season should have an inconsequential impact on mortality.

5.2 The Food-Security Channel

The timing of extreme weather is important. A look at Figures 18 through 21 validates once more the negative effect of high temperatures on mortality, *provided that such high temperatures take place during the growing season.* This effect is statistically significant for rural areas, but not for urban areas, which suggests that rural specialization in agriculture may explain differences in mortality rates, as discussed above. Even though signs and magnitudes seem to be correct for the temperature impacts during the non-growing season, the null hypothesis of equality with the base category is not rejected for most of the temperature ranges. The three higher temperature ranges for rural areas are statistically different from zero: an additional single day with temperatures higher than 26°C increases mortality on average by 0.2 percent, relative to the base category of 16°C-18°C, which indicates that virtually all the effect that temperature exerts on mortality is explained by the occurrence of extreme events during the growing season. Precipitation impacts are generally insignificant at the conventional levels, both for urban and rural areas, regardless of the timing of rainfall.

Figures 22-24 point to a similar conclusion in terms of the effect of weather on agricultural output. Notice that the effect of extreme weather on agricultural output is not apparent at first sight. The number of extreme hot (or cold) days in a given agricultural year does not seem to have a significant impact on agricultural output (see Figure 22.) However, when the regressors consist of temperature ranges for growing-season days only, a clear negative relationship emerges: the higher the temperature, the lower the agricultural output (see Figure 23.) On the contrary, as expected, when I regress agricultural productivity against non-growing-season temperature ranges, there is no relationship between temperature and agricultural output that is statistically significant at the conventional levels, which is reflected in the fairly flat line shown in Figure 24. As in the mortality analysis, the relationship between precipitation and agricultural output, as modeled, yields insignificant results.

It is important to notice that, because of the reduced number of observations per range (instead of 365 days per year, the growing season, as defined, has 153 days, while the non-growing season comprises only 120 days), parameter estimation precision is reduced. Yet, I find the same results when estimating equation (9) for urban and rural areas (see Table 6.) In terms of temperature, hot weather is substantially more dangerous than cold temperatures in Mexico. Again, severe temperature impacts on mortality are typically zero or slightly positive during the non-growing season. Conversely, they are large in magnitude and statistically significant during the growing season (with the exception of cold weather in rural areas, whose impact is statistically zero.)

Similarly, extreme precipitation patterns have a more profound mortality impact in rural areas, with rural-mortality estimates being approximately three times larger than urban ones. Cumulative-millimeter-day variables are always significant for the growing-season specifications, but typically equal to zero in statistical terms for the non-growing season regressions.

An analysis of key variables of the agricultural cycle provides further evidence of the food-security channel being at work. Table 7 presents estimates of the impact of extreme temperatures on agricultural output, agricultural productivity, and crop prices, both for the growing and the non-growing season, based only on equation (9), given the estimate precision issues pointed out above. It is worth noting that these results support the food-security channel hypothesis: extreme weather is indeed negatively affecting productivity and prices. In turn, as the abundant literature on famines, food supply chains, and agroecology has repeatedly shown, this reduces income and consumption.

Columns (1) and (2) in Table 7 report the impact of extreme weather on agricultural income. In terms of temperature, the findings are similar to those of the mortality analysis in the previous section. Extreme heat, operationalized as the number of cumulative-degree-days above 30°C, is associated with lower agricultural income, and the association is significant at the conventional levels. This is true for the growing season, but not so for the non-growing season. In effect, while one additional degree-day above 30°C during the growing season leads to a 5 percent decrease in agricultural income, one extra degree-day above 30°C during the non-growing season has an effect that is not statistically different from zero. Once again, consistent with the results of the mortality analysis, cold days do not seem to have an impact, either during the growing season or during the non-growing season, on agricultural income. With regard to the precipitation variables, both "dry" and "wet" days during the growing season lead to decreases in income. Both coefficients are negative and statistically significant, but dry days are roughly three times more damaging than wet days: an additional millimeter-day above 8 mm. is associated with a 0.04 percent decrease in output, while an additional millimeter-day below 3 mm. is associated with a 0.13 percent decrease in income. Conversely, precipitation impact estimates for the non-growing-season regression are statistically equal to zero.

Columns (3) and (4) in Table 7 replicate this exercise for agricultural productivity, measured as the value of output per cultivated hectare. The impact of extreme weather on productivity is very similar to that on agricultural income. First, notice that severe precipitation and temperatures taking place during the non-growing season do not seem to have a significant effect on agricultural productivity. The null hypothesis of equality to zero is not rejected for any weather coefficient. Second, the effect of abnormally high and low temperatures on productivity is negative, and comparable in magnitude to the effect on agricultural output, but not statistically significant. Finally, both the coefficients for the cumulative-millimeter-days above 8 mm. and the cumulative-millimeter-days below 3 mm. are, as expected, negative and significant at the conventional levels, with productivity decreases ranging from 0.02 percent in the case of an extra millimeter above 8 mm/day to 0.08 percent for the case of an additional millimeter below 3mm/day.

Table 8 presents more specific results for yields, defined as tons per cultivated hectare, for five of the most important crops in Mexico: corn, beans, chilies, tomato, and wheat, for which sufficient data are available. Together, these crops make up more than 55 percent of the total value of agricultural output of the country. Columns (1) through (6) show the results of estimating equation (8.) As in previous versions of equation (8), moderate temperature and precipitation ranges are, in general, equal to the reference range, so that I present only the three most extreme ranges at both ends of the distribution for the sake of conciseness. An analogous pattern to previous estimations arises: cold temperatures usually do not have a significant effect on yields; if anything, colder temperatures increase yields. Severely hot temperatures, on the contrary, do seem to impact crop yields negatively. For the five crops analyzed, all show a clear negative relation between temperature and yields, and three are statistically significant at the conventional levels. In the case of Mexico's staple crop, corn, for which the largest number of observations is available, an additional day in any of the three coldest temperature ranges leads to an approximate yield increase of 0.1 percent relative to the reference temperature range of 16°-18°C. Conversely, an additional day in any of the three hottest temperature ranges, leads, on average, to a 0.1 percent yield decrease relative to the reference temperature range. For other crops, the impact of hot temperatures is even more acute: for instance, one single day with temperatures higher than 30°C leads to a 0.3 percent decrease in tomato yields and to a 0.5 percent decrease in wheat yields.

The results of precipitation ranges are fairly parallel to those of temperature extremes. Precipitation ranges below 4 mm., with the exception of the wheat regression, are negative and generally significant. Days with limited rainfall, relative to the reference precipitation range, lead to yield decreases ranging from 0.2 percent to 0.9 percent. Days with extreme rainfall, relative to the reference precipitation range, lead to yield decreases ranging from 0.4 percent to 3 percent. Once again, taking as an example the representative case of corn, an additional day in the 0 mm. range leads to a 0.2 percent yield decrease (relative to the reference category of 6-8 mm.), while an extra day with rainfall surpassing 30 mm. leads to a 0.4 percent yield decrease.

If extreme weather, both in terms of precipitation and temperature, leads to decreases in output, yields and productivity, then price increases ought to be expected. The price mechanism in market economies adjusts in response to constraints in crop supplies. Columns (5) and (6) in Table 7 present the results of estimating equation (9) for a bundle of agricultural prices for 10 representative crops that make up approximately 70 percent of the total value of agricultural production in Mexico (Servicio de Información Agroalimentaria y Pesquera 2012.)

Indeed, extreme weather does increase agricultural prices, with hot temperatures being the weather condition that exacerbates prices most. This pattern once again holds for the growing season only. An additional degree-day above 30°C is associated with a sharp 7 percent increase in crop prices. Any other severe weather impact is considerably weaker. An additional degree-day below 10°C leads to a 0.4 percent increase in agricultural prices. Likewise, an extra millimeter-day above the 8 mm. threshold is associated with a 0.02 percent increase in crop prices, while an extra millimeter-day below the 3 mm. threshold leads to an increase of approximately 0.06 percent in agricultural prices. Unsurprisingly, when agricultural income and productivity seems to be unaffected by weather, that is, during the non-growing season, prices are not affected by severe climate either.[13]

6 Conclusion

Extreme weather exerts negative effects on humans, particularly on the most vulnerable. Using data for all the 2,454 municipalities of Mexico for the period 1980-2010, I analyze the impact of exposure to severe weather, defined for the purposes of this paper as extreme temperatures and precipitation, on death and agricultural outcomes.

I present empirical evidence for the hypothesis that extreme weather increases mortality rates and decreases agricultural income and productivity, in addition to increasing crop prices. In particular, I find that extreme heat is the most damaging form severe weather may take. I find that extremely hot temperatures increase mortality and crop prices, while they at the same time decrease agricultural income, agricultural productivity, and yields of critical crops, such as corn, which a large number of poor households in rural Mexico depend upon for their subsistence. As expected, given that Mexico does not have harshly cold seasons, I do not find any statistically significant effect of cold weather on health or agricultural outcomes. I find that precipitation extremes have an ambiguous effect on mortality depending on the model specification. Evidence is more coherent in terms of agricultural outcomes, as I find that both limited and extreme rainfall pose negative consequences for crop yields, agricultural in-

[13] The findings throughout this paper should be interpreted taking into account the inherent limitations of the empirical specification. For instance, given that I estimated the effect of weather on mortality based on inter-annual climate variation, the estimates should be understood as short-term impacts of unanticipated severe weather, which provide an upper-bound to the impact of less unpredictable extreme weather. As Burgess et al. (2011, p. 33) point out: "individuals are likely to be better able to adapt to long-run, predictable change, for example through migration (for example, from rural to urban areas), technology adoption, or occupational change away from climate-exposed industries such as agriculture."

comes and productivity, with these effects being observed during the growing season only.

I find that rural areas are substantially more vulnerable to severe weather than urban areas. In addition, I also find that, for rural areas, if extreme weather takes place during the peak of the growing season, the effects are considerably stronger than in a situation where climate extremes are observed during non-growing times. This echoes the conclusion of Burgess et al. (2011) for their study in India. As they put it: "quasi-random weather fluctuations introduce a lottery in the survival chances of citizens. But this lottery only affects people living in the rural parts where agricultural yields, wages and prices are adversely affected by hot and dry weather" (p. 34.)

These results have an important policy implication: under severe weather conditions, a free market economy can produce socially unfair outcomes. In particular, climate extremes cause crop prices to rise precisely when incomes fall (farmers have less output, productivity falls), which in an extreme situation may lead to death, as evidenced in this paper. In other words, the price mechanism aggravates the problem instead of being self-correcting. Technically speaking, the problem is one of missing markets rather than market failure: if regions specialized in agriculture (usually rural communities) had sufficient insurance and credit mechanisms catering to the poor, these would provide safety nets in the event of a weather shock. As a result, the government may play a key role in creating the conditions to mitigate the adverse effects of climate, even though these risks cannot be fully eliminated.

Furthermore, if extreme heat is the most lethal mechanism through which weather affects human physiology, and this impact is considerably stronger in rural regions, given their dependence on agriculture, the consequences of climate change are likely to be unevenly distributed across communities. Empirical evidence indicates that there has been an overall decrease in the number of cold days, while the number of warm spells and heat waves has increased (IPCC 2012.) As a result, development policy must encompass differential vulnerability and capacity mechanisms in order for communities to better adapt to these changing conditions. Future research should focus on these environmental and institutional aspects.

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Table 1. Mortality Rates in Mexico, 1990-2010, by Type of Area

	Pooled (1)	Rural (2)	Urban (3)
Crude mortality rate	4.8	9.1	4.9
	(1.4)	(34.5)	(1.9)
Infant mortality rate	15.4	31.6	19.8
	(9.6)	(160.3)	(64.9)
Fetal mortality rate	10.5	16.4	13.6
	(6.7)	(99.6)	(51.5)

Note: Municipalities may consist of urban areas only, rural areas only, or a combination of both. All statistics are weighted by total municipal population. Standard deviations in parentheses.

Table 2. Household Income and Expenditures (in Mexican Pesos), by Type of Household

	Income (1)	Expenditures (2)	Food Consumption (3)	% Households Employed in Agriculture (4)
Pooled	11,667	7,964	2,607	18.9
Urban	13,026	8,878	2,816	7.2
Rural	6,673	4,602	1,839	61.9

Source: Encuesta Nacional de Ingresos y Gastos de los Hogares 2010.

Table 3. Relevant Agricultural Outcomes in Mexico, 1994-2009, by Type of Area

	Pooled (1)	Rural (2)	Urban (3)
Agricultural output ($1,000)	658,092.4	664,831.9	84,092.1
	(1959499)	(1969799)	(259492)
Agricultural productivity	21.5	21.6	11.9
($/ha)	(817.3)	(822.0)	(54.1)
Harvested hectares (ha)	36,791.8	37,154.2	6,388.6
	(46923)	(47070)	(10285)
Yield (corn) (tons/ha)	2.7	2.7	1.3
	(2.1)	(2.1)	(0.9)
Volume (corn) (tons)	54,114.5	54,709.9	1,138.9
	(155137)	(155904)	(1740)
Price index	2.3	2.3	2.3
	(2.2)	(2.2)	(2.3)

Note: If fewer than 2,500 residents live in a given municipality, such a municipality is considered "rural." Data refer to the agricultural cycle, rather than calendar years. Monetary values are in thousands of pesos of 2009. All statistics are weighted by total harvested hectares, except descriptive statistics for corn, which are weighted by harvested hectares of corn. Standard deviations in parentheses.

Table 4. Extreme Weather in Mexico, 1979-2009, by Type of Area

Rates	Pooled (1)	Rural (2)	Urban (3)
Daily mean temperature (°C)	18.5	17.4	18.5
	(4.4)	(3.9)	(4.4)
Annual average rainfall (mm)	712.8	678.9	713.0
	(419.1)	(332.7)	(419.5)
Annual degree-days (over 30°C)	11.6	6.8	11.6
	(45.5)	(30.0)	(45.5)
Annual degree-days (below 10°C)	30.1	38.7	30.1
	(54.7)	(57.8)	(54.7)
Annual millimeters-days (over 8mm)	174.8	129.3	175.1
	(225.1)	(139.8)	(225.4)
Annual millimeters-days (below 3mm)	779.7	764.9	779.8
	(122.7)	(120.6)	(122.8)

Note: If fewer than 2,500 residents live in a given municipality, such a municipality is considered "rural." All statistics are weighted by total municipal population. Standard deviations in parentheses.

Table 5. Estimates of the Impact of Extreme Weather on Relevant Mortality Rates

	Crude mortality	Infant mortality	Fetal mortality	Urban mortality	Rural mortality
	(1)	(2)	(3)	(4)	(5)
Cumulative-degree-days above 30	0.00022 ***	0.00038 **	0.00008	0.00018 **	0.00034 *
	(0.00007)	(0.00019)	(0.00028)	(0.00007)	(0.00021)
Cumulative-degree-days below 10	0.00004	-0.00017	-0.00041 **	0.00005	-0.00028
	(0.00005)	(0.00012)	(0.00018)	(0.00009)	(0.00022)
Cumulative-mm-days above 8	0.00010 ***	0.00006 *	-0.00017 ***	0.00003 **	0.00022 ***
	(0.00001)	(0.00003)	(0.00004)	(0.00002)	(0.00004)
Cumulative-mm-days below 3	0.00019 ***	-0.00004	-0.00021 ***	0.00012 ***	0.00040 ***
	(0.00003)	(0.00007)	(0.00008)	(0.00004)	(0.00009)
N	48,583	40,425	35,104	29,206	46,384

Note: Response variables are in logs. Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by total municipal population. Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6. Estimates of the Impact of Extreme Weather on Relevant Mortality Rates, by Season

	Agricultural year				Growing season				Non-growing season			
	Urban mortality		Rural mortality		Urban mortality		Rural mortality		Urban mortality		Rural mortality	
	(1)		(2)		(3)		(4)		(5)		(6)	
Cumulative-degree-days above 30	0.00018	**	0.00034	*	0.02484	***	0.06166	***	0.00017	**	0.00022	
	(0.00007)		(0.00021)		(0.00649)		(0.00821)		(0.00008)		(0.00022)	
Cumulative-degree-days below 10	0.00005		-0.00028		0.00261	**	0.00014		0.00002		-0.00016	
	(0.00009)		(0.00022)		(0.00122)		(0.00190)		(0.00010)		(0.00025)	
Cumulative-millimeter-days above 8	0.00003	**	0.00022	***	0.00001		0.00033	***	0.00013	***	0.00009	
	(0.00002)		(0.00004)		(0.00003)		(0.00008)		(0.00005)		(0.00009)	
Cumulative-millimeter-days below 3	0.00012	***	0.00040	***	0.00019	***	0.00070	***	-0.00006		0.00063	**
	(0.00004)		(0.00009)		(0.00006)		(0.00014)		(0.00013)		(0.00031)	
N	29,206		46,384		29,206		46,384		29,206		46,384	

Note: Response variables are in logs. Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by total municipal population. Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7. Estimates of the Impact of Extreme Weather on Relevant Agricultural Outcomes, by Season

	Agricultural income				Agricultural productivity (output/ha)				Crop prices			
	Growing season		Non-growing season		Growing season		Non-growing season		Growing season		Non-growing season	
	(1)		(2)		(3)		(4)		(5)		(6)	
Cumulative-degree-days above 30	-0.04935	**	0.00030		-0.05122		0.00102		0.06983	***	-0.00066	
	(0.02298)		(0.00057)		(0.03389)		(0.00055)		(0.01951)		(0.00040)	
Cumulative-degree-days below 10	0.00014		0.00054		-0.00556		0.00046		0.00407	*	-0.00000	
	(0.00373)		(0.00035)		(0.00344)		(0.00034)		(0.00241)		(0.00024)	
Cumulative-millimeter-days above 8	-0.00040	***	-0.00056		-0.00024	**	-0.00055		0.00017	**	0.00011	
	(0.00010)		(0.00043)		(0.00010)		(0.00043)		(0.00008)		(0.00023)	
Cumulative-millimeter-days below 3	-0.00133	***	-0.00148		-0.00079	***	-0.00112		0.00056	**	0.00076	
	(0.00030)		(0.00121)		(0.00031)		(0.00123)		(0.00023)		(0.00055)	
N	27,562		27,562		27,562		27,562		27,715		27,715	

Note: Response variables are in logs. Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by total harvested hectares. Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8. Estimates of the Impact of Extreme Weather on Relevant Crop Yields (tons/ha)

	Impact on log crop yields											
	Days < 10℃		Days 10°-12℃		Days 12°-14℃		Days 26°-28℃		Days 28°-30℃		Days > 30℃	
	(1)		(2)		(3)		(4)		(5)		(6)	
Corn	0.00123	***	0.00089	**	0.00103	***	-0.00155	***	-0.00093	**	-0.00066	*
(n=26,343)	(0.00039)		(0.00036)		(0.00027)		(0.00036)		(0.00043)		(0.00036)	
Beans	0.00237	***	-0.00041		0.00113		-0.00259	***	-0.00159	*	-0.00258	**
(n=20,054)	(0.00075)		(0.00091)		(0.00089)		(0.00099)		(0.00093)		(0.00107)	
Chillies	-0.00003		-0.00496	**	0.00265		-0.00107		-0.00107		-0.00103	
(n=7,863)	(0.00239)		(0.00206)		(0.00232)		(0.00226)		(0.00217)		(0.00225)	
Tomato	-0.00393	***	-0.00012		0.00066		-0.00117		-0.00122		-0.00099	
(n=6,270)	(0.00152)		(0.00129)		(0.00099)		(0.00132)		(0.00115)		(0.00186)	
Wheat	0.00020		-0.0018		0.00079		-0.00101		-0.00443	**	-0.00511	***
(n=6,261)	(0.00074)		(0.00084)		(0.00056)		(0.00125)		(0.00221)		(0.00188)	

Table 8., continued

	Impact on log crop yields											
	Days 0mm		Days 0-2mm		Days 2-4mm		Days 26-28mm		Days 28-30mm		Days $>$ 30mm	
	(1)		(2)		(3)		(4)		(5)		(6)	
Corn	-0.00183	**	-0.00219	***	-0.00265	***	-0.00728		0.00300		-0.00386	*
(n=26,343)	(0.00077)		(0.00082)		(0.00096)		(0.00491)		(0.00871)		(0.00200)	
Beans	-0.00205		-0.00232		-0.00076		-0.00133		0.01481		-0.00436	
(n=20,054)	(0.00268)		(0.00262)		(0.00355)		(0.00615)		(0.00952)		(0.00365)	
Chillies	-0.00671	**	-0.00648	**	-0.00875	**	-0.00020		-0.01627		0.00087	
(n=7,863)	(0.00285)		(0.00294)		(0.00350)		(0.01243)		(0.01491)		(0.00727)	
Tomato	-0.00260		-0.00304		-0.00251		-0.02802	**	0.00606		-0.01581	**
(n=6,270)	(0.00246)		(0.00240)		(0.00293)		(0.01156)		(0.01396)		(0.00652)	
Wheat	0.00516	***	0.00617	***	0.00503	**	0.02770	***	0.03279	***	-0.01076	**
(n=6,261)	(0.00188)		(0.00189)		(0.00203)		(0.01035)		(0.01228)		(0.00543)	

Note: Response variables are in logs. Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by each crop's total harvested hectares. Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

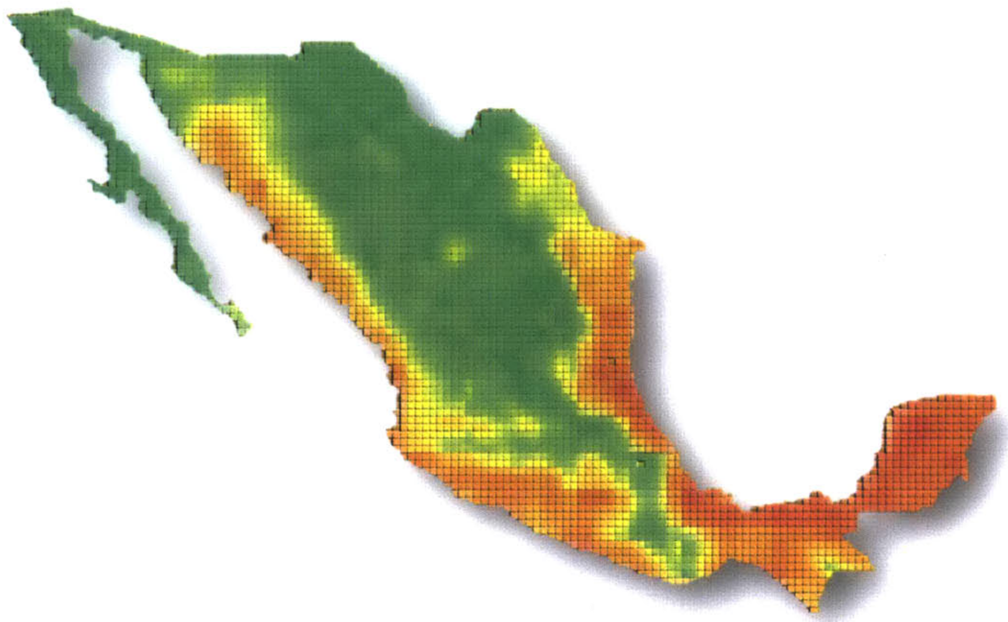

Figure 1. Probability of infectious-disease outbreaks due to severe weather events
Note: Areas with a high probability of infectious-disease outbreaks resulting from severe weather are shown in red; areas with low probability in green.

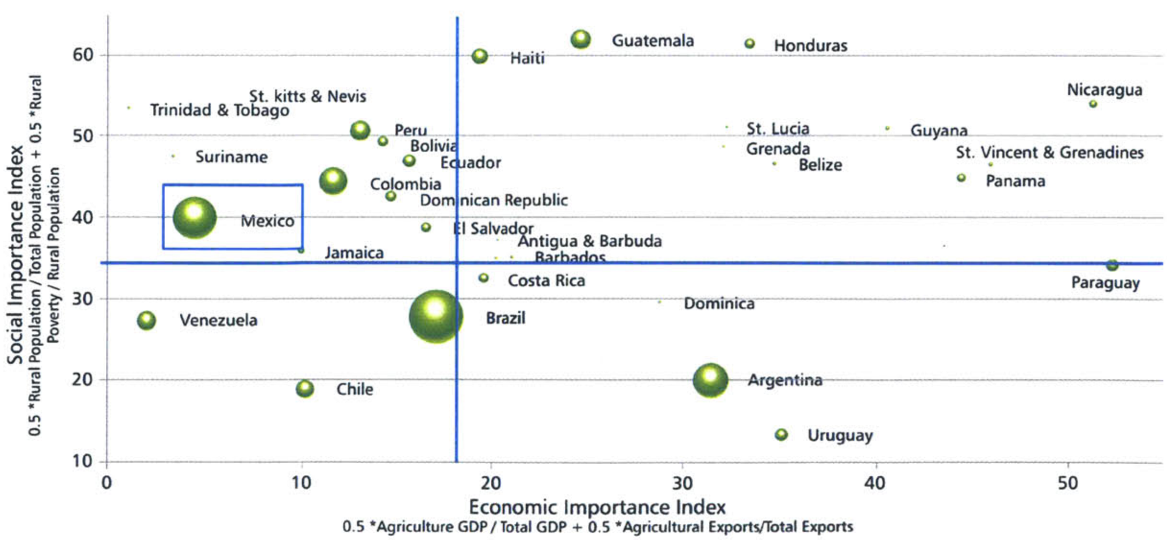

Figure 2. Economic and social importance of the agricultural sector, Latin American countries
Source: World Bank (2010)
Note: Size of the balloons represents the level of agricultural gross domestic product.

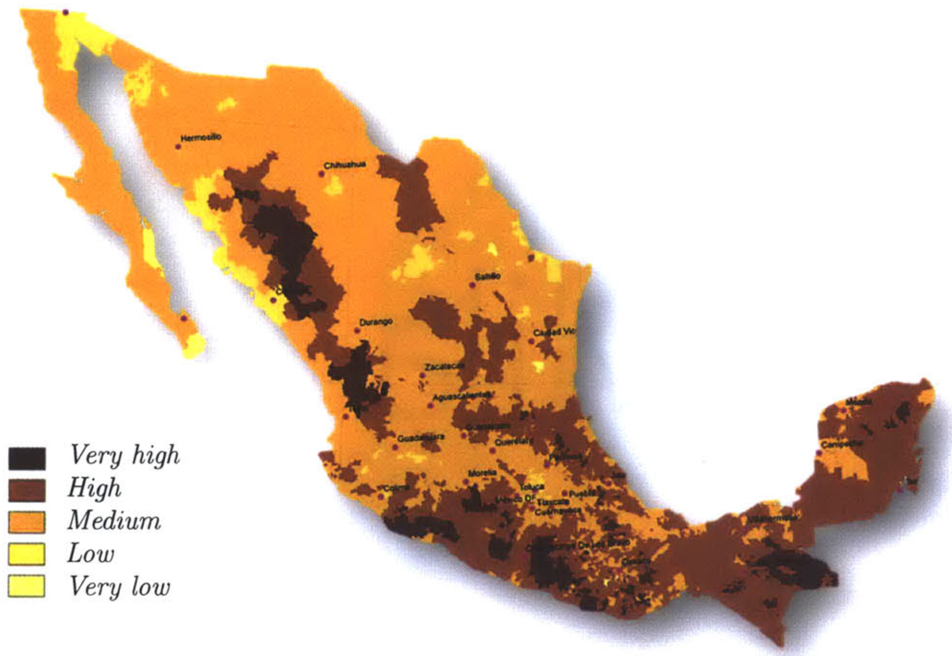

Figure 3. Agricultural vulnerability, by municipality
Source: Instituto Mexicano de Tecnología del Agua (2010)

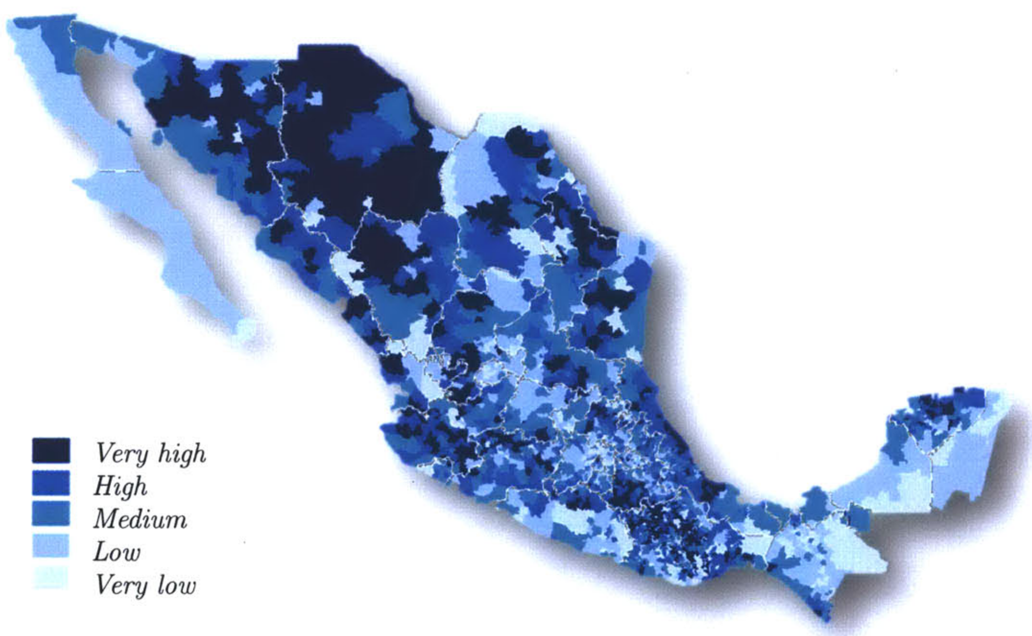

Figure 4. Crude (all-cause) mortality rate, by municipality, 2010

Figure 5. Infant mortality rate, by municipality, 2010

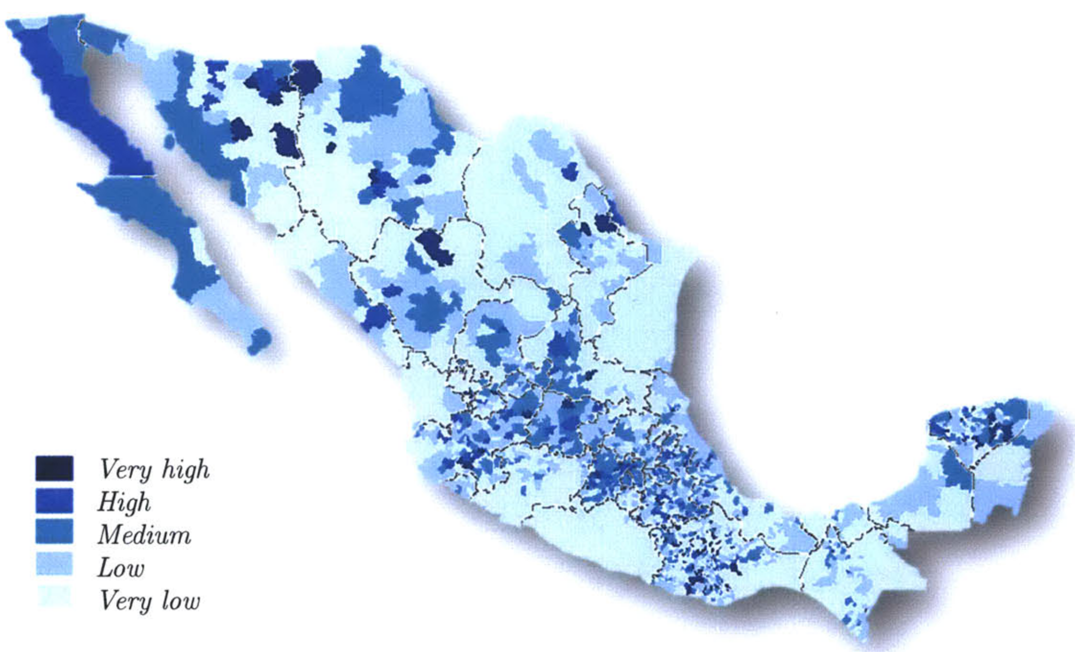

Figure 6. Perinatal mortality rate, by municipality, 2010

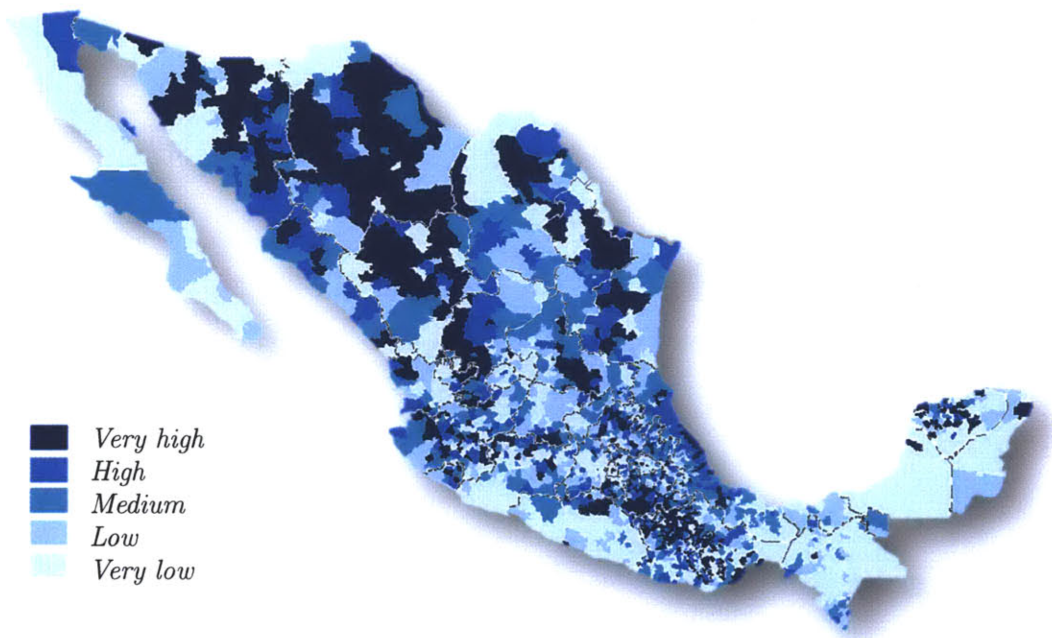

Figure 7. Rural mortality rate, by municipality, 2010

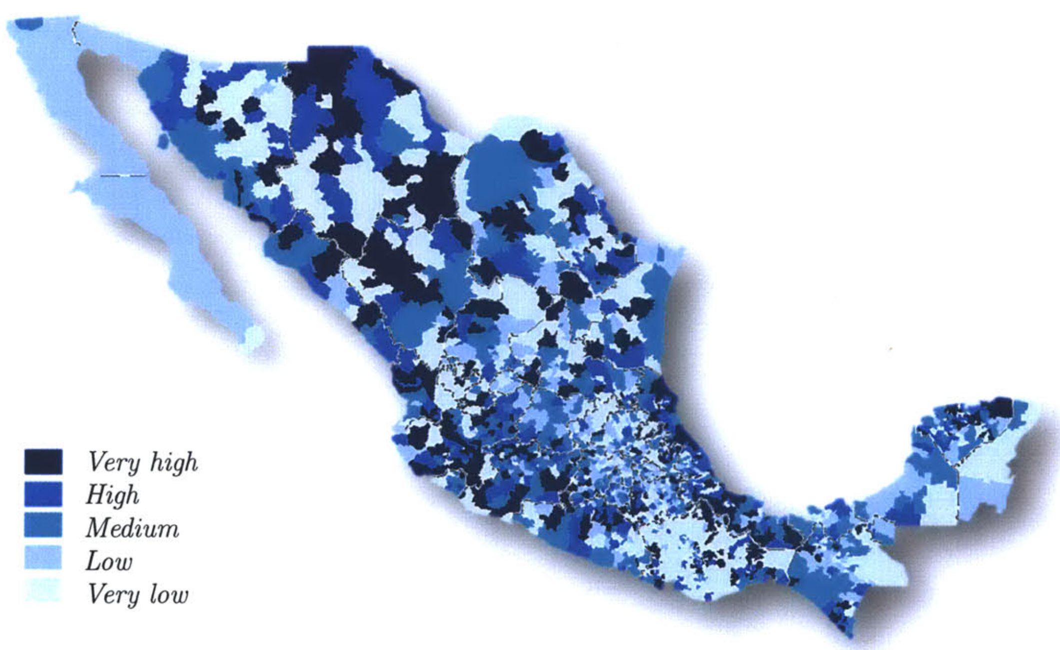

Figure 8. Urban mortality rate, by municipality, 2010

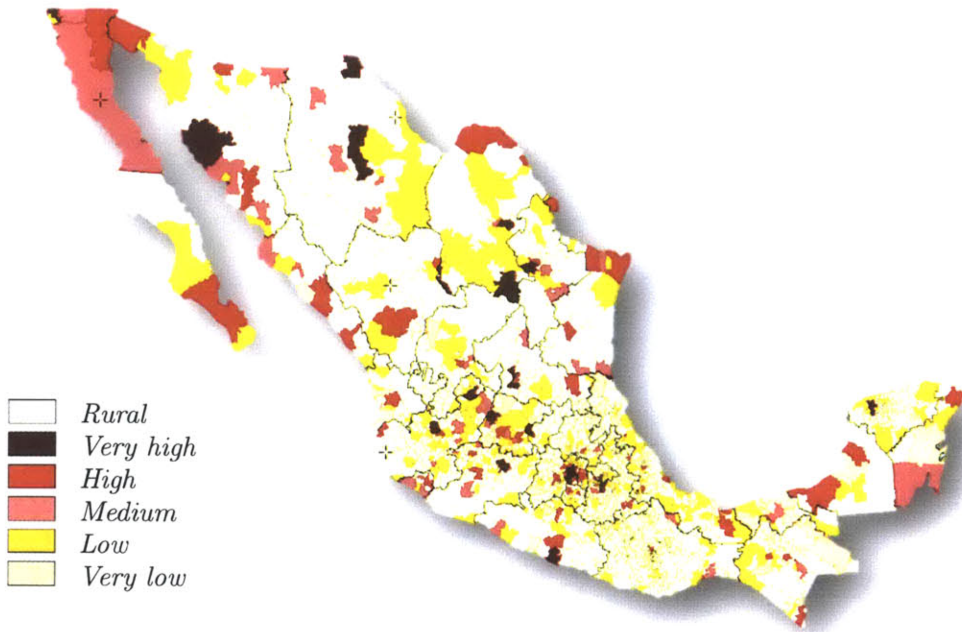

Figure 9. Urbanization in Mexico, by municipality, 2000
Source: Instituto Nacional de Ecología y Cambio Climático (2013)

Figure 10. Economic sector specialization in Mexico, by municipality, 2000
Source: Instituto Nacional de Ecología y Cambio Climático (2013)
Note: *A*: Agriculture; *Q*: mining and quarrying; *M*: manufacturing; *S*: services.

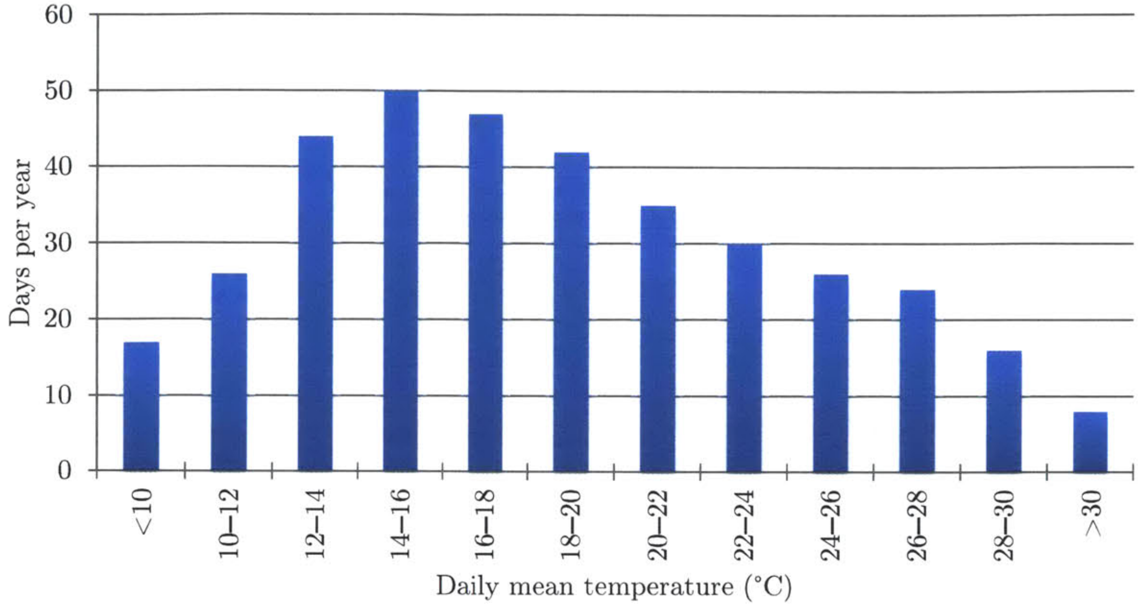

Figure 11. Temperature distribution in Mexico, 1979-2010

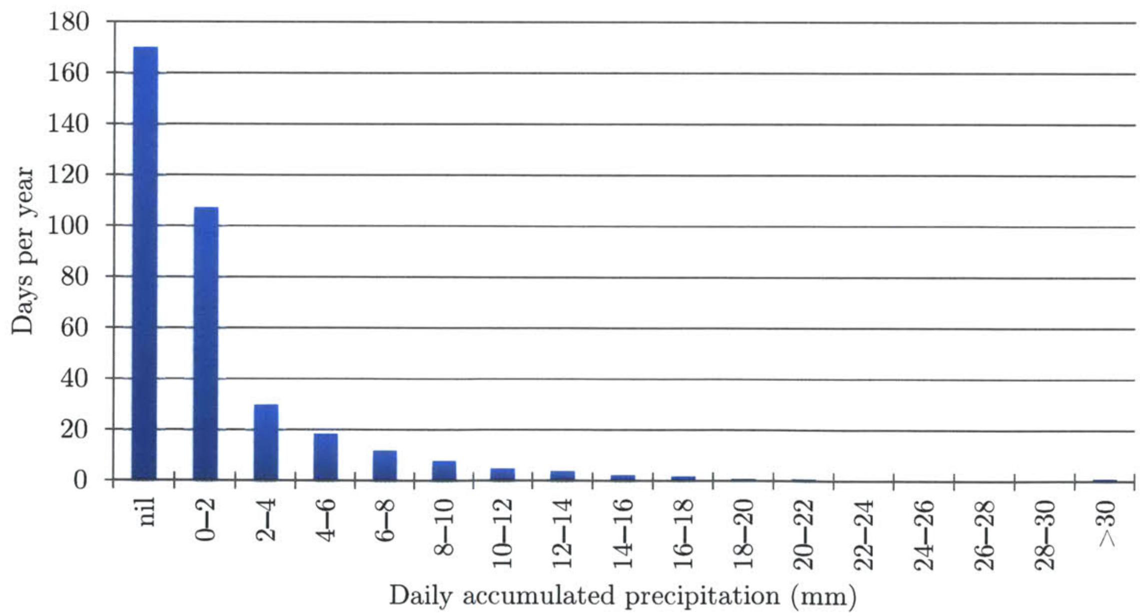

Figure 12. Rainfall distribution in Mexico, 1979-2010

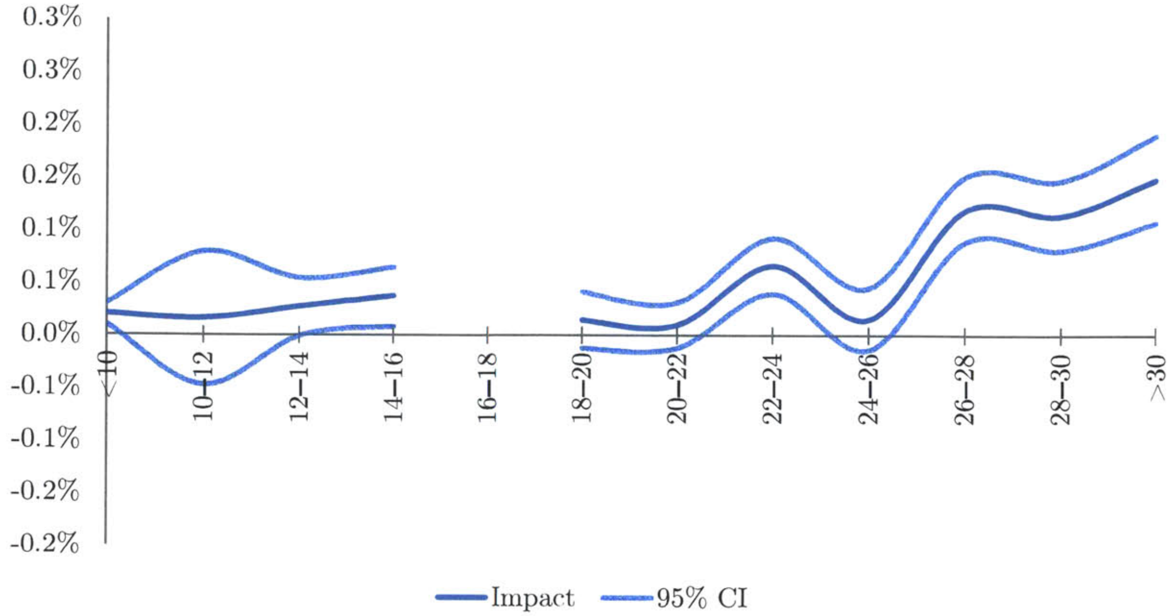

Figure 13. Estimated impact of a day in 12 temperature ranges on log annual mortality rate, relative to a day in the 16°-18°C range

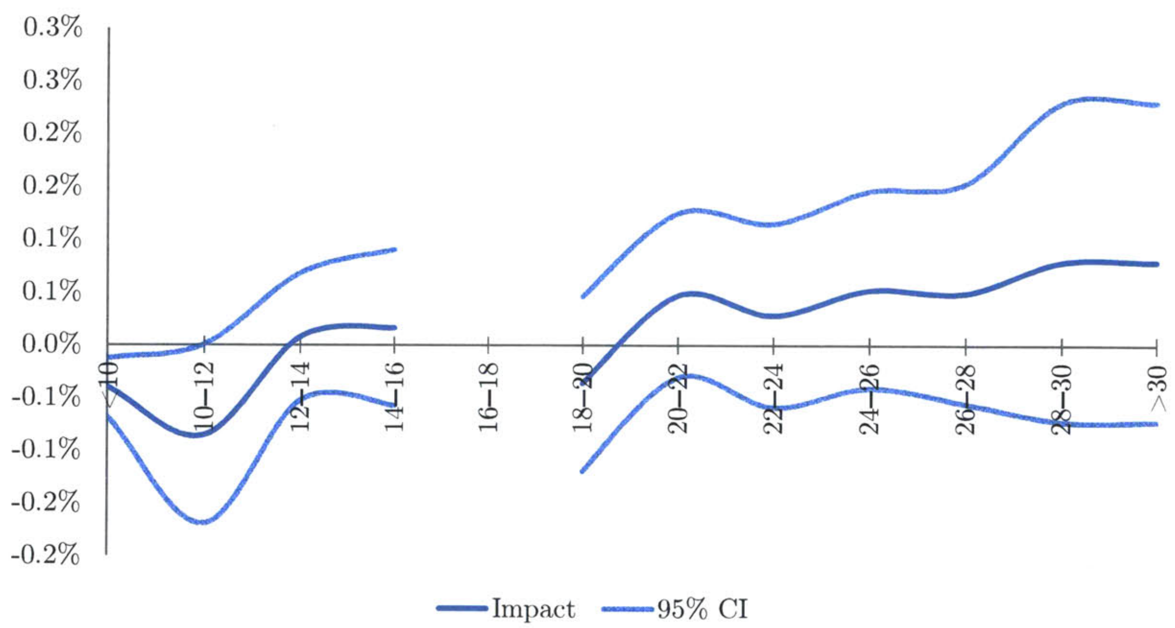

Figure 14. Estimated impact of a day in 12 temperature ranges on log annual fetal mortality rate, relative to a day in the 16°-18°C range

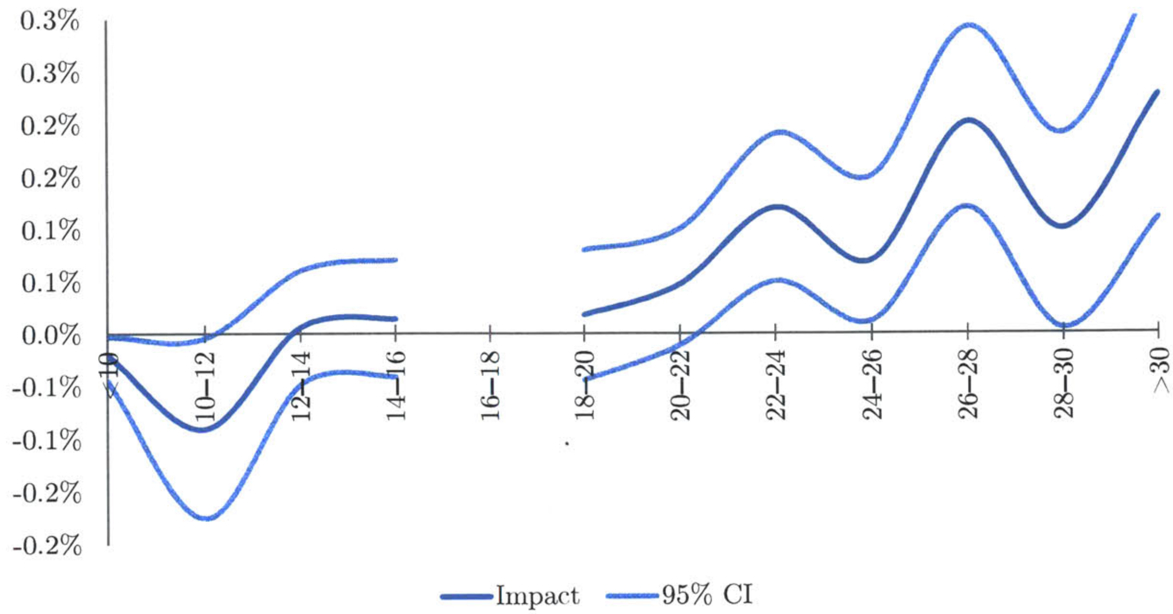

Figure 15. Estimated impact of a day in 12 temperature ranges on log annual infant mortality rate, relative to a day in the 16°-18°C range

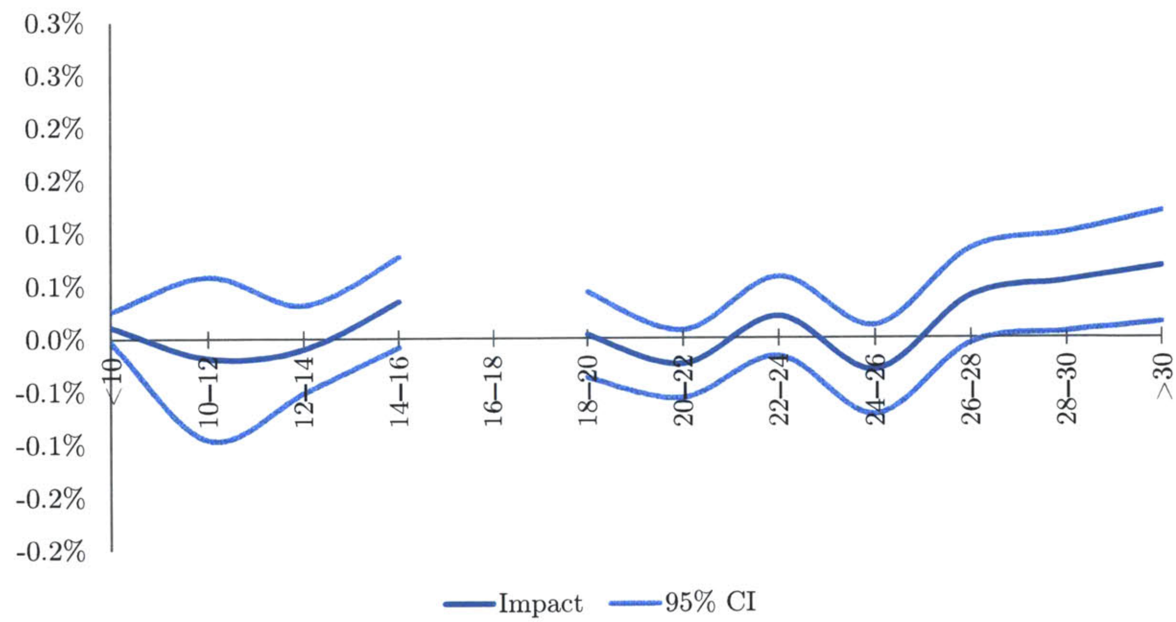

Figure 16. Estimated impact of a day in 12 temperature ranges on log annual urban mortality rate, relative to a day in the 16°-18°C range

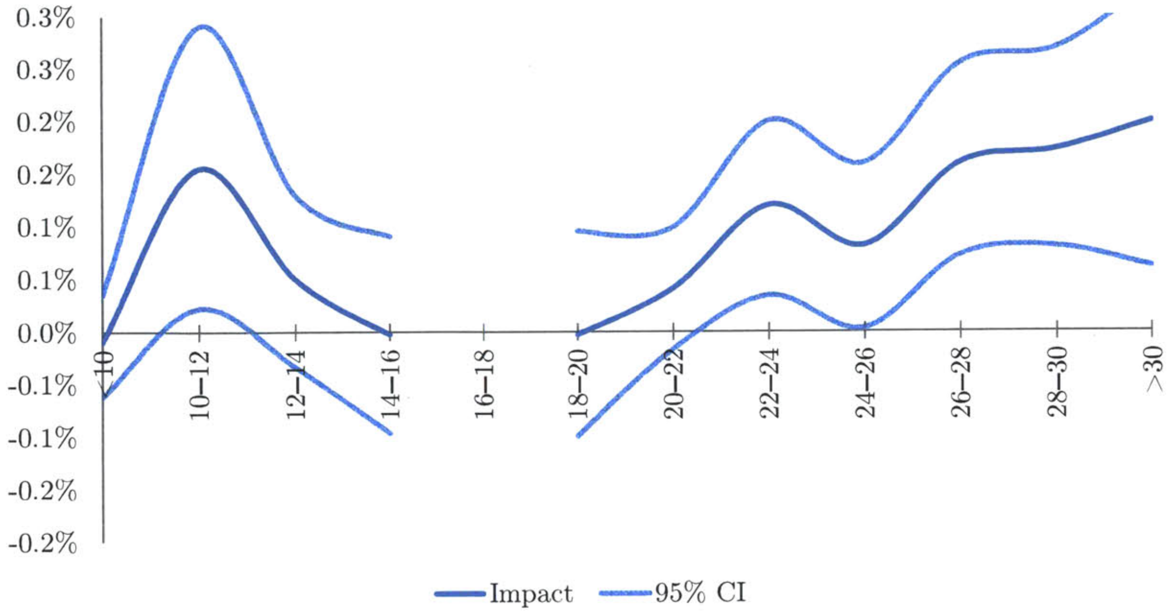

Figure 17. Estimated impact of a day in 12 temperature ranges on log annual rural mortality rate, relative to a day in the 16°-18°C range

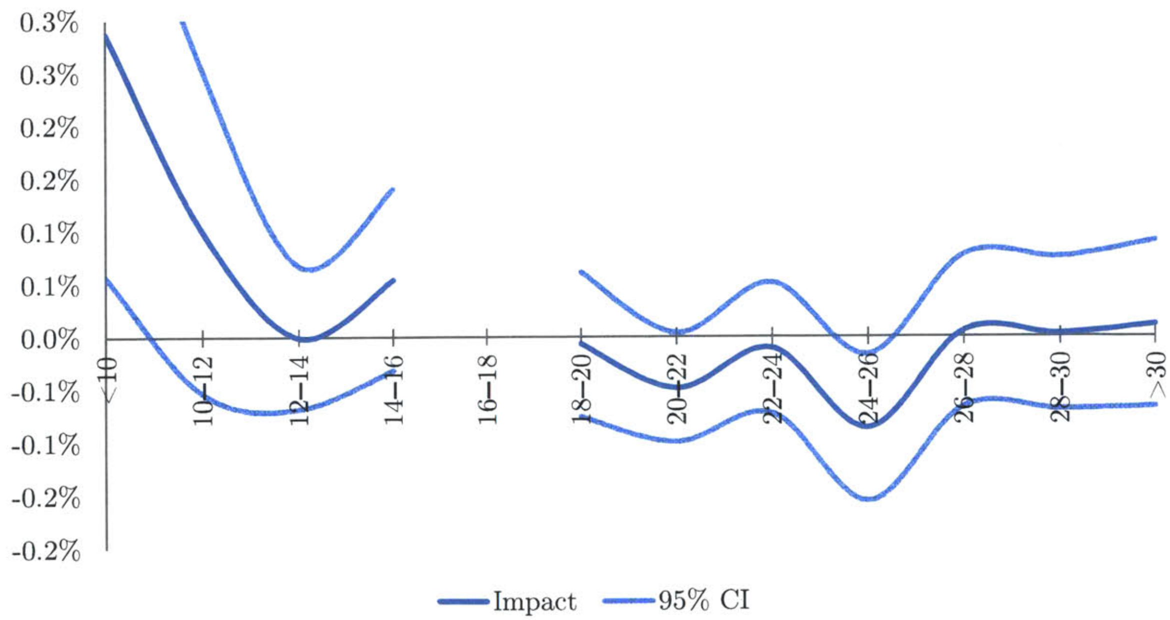

Figure 18. Estimated impact of a growing-season day in 12 temperature ranges on log annual urban mortality rate, relative to a day in the 16°-18°C range

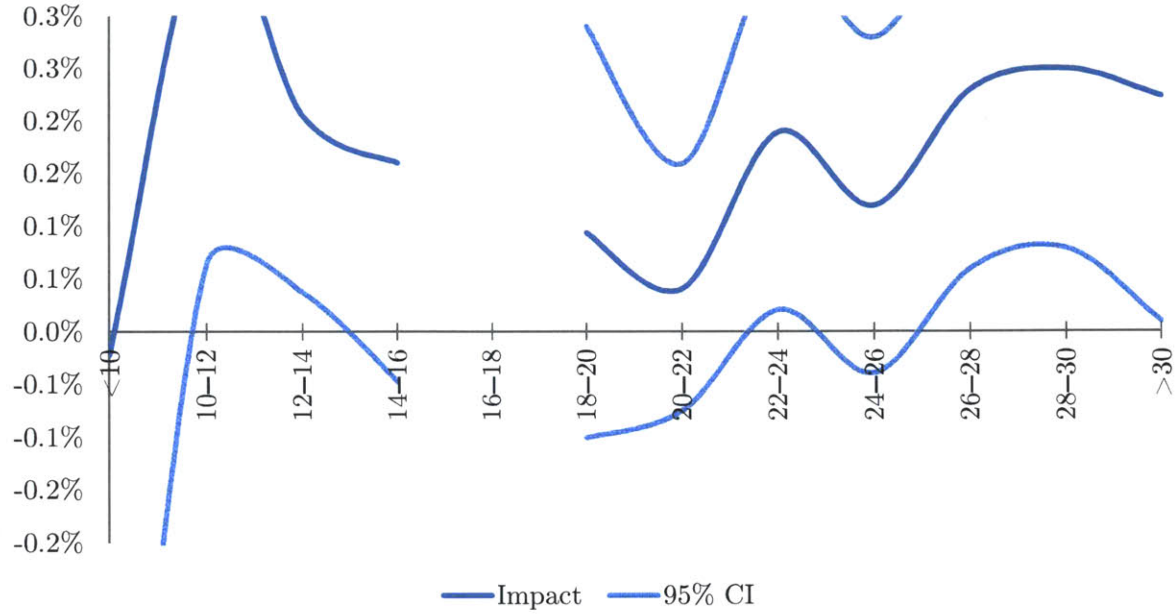

Figure 19. Estimated impact of a growing-season day in 12 temperature ranges on log annual rural mortality rate, relative to a day in the 16°-18°C range

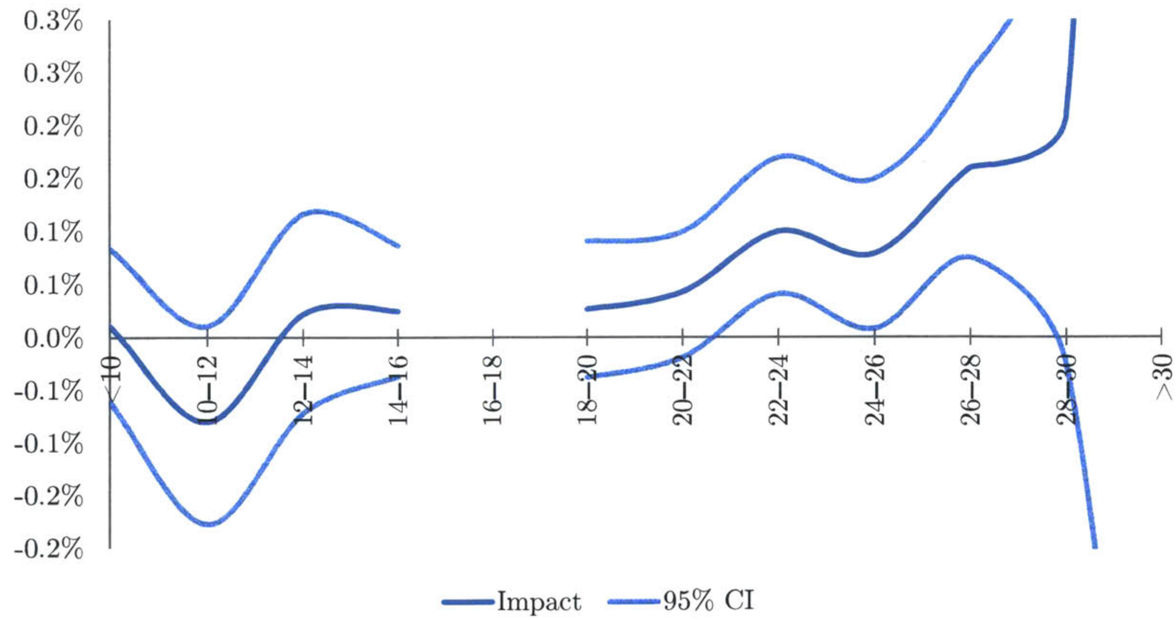

Figure 20. Estimated impact of a non-growing-season day in 12 temperature ranges on log annual urban mortality rate, relative to a day in the 16°-18°C range

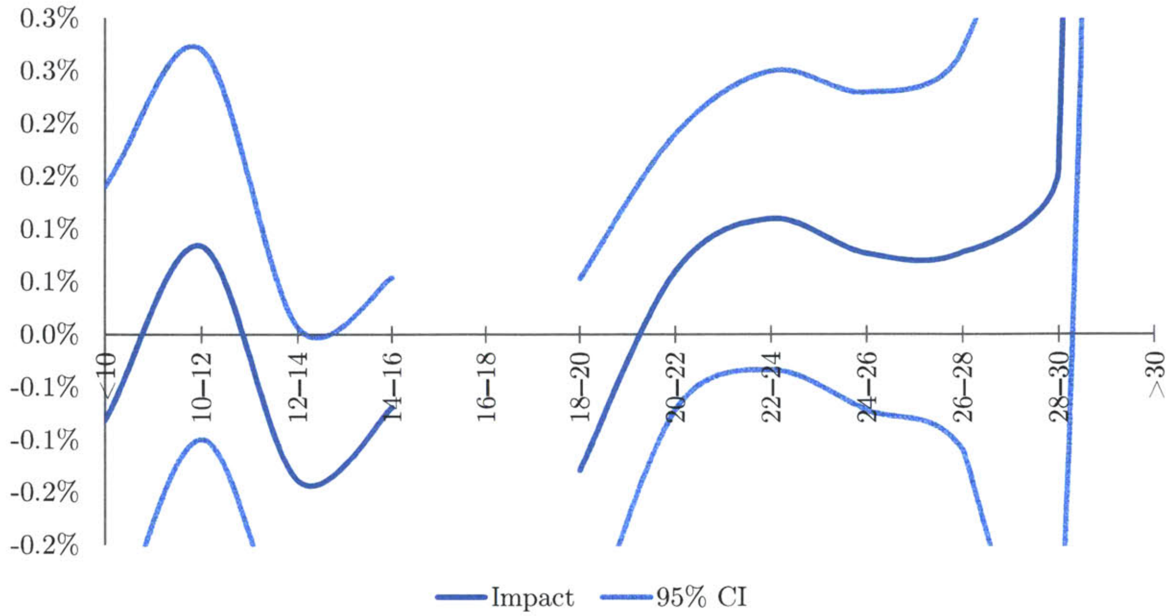

Figure 21. Estimated impact of a non-growing-season day in 12 temperature ranges on log annual rural mortality rate, relative to a day in the 16°-18°C range

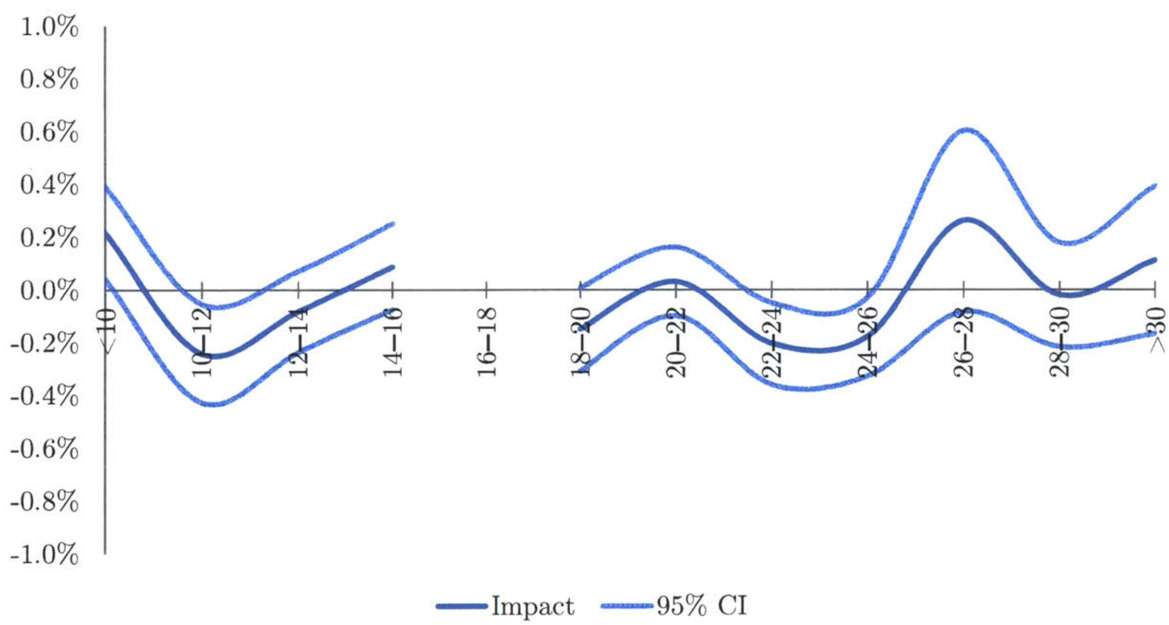

Figure 22. Estimated impact of a day in 12 temperature ranges on log annual agricultural output, relative to a day in the 16°-18°C range

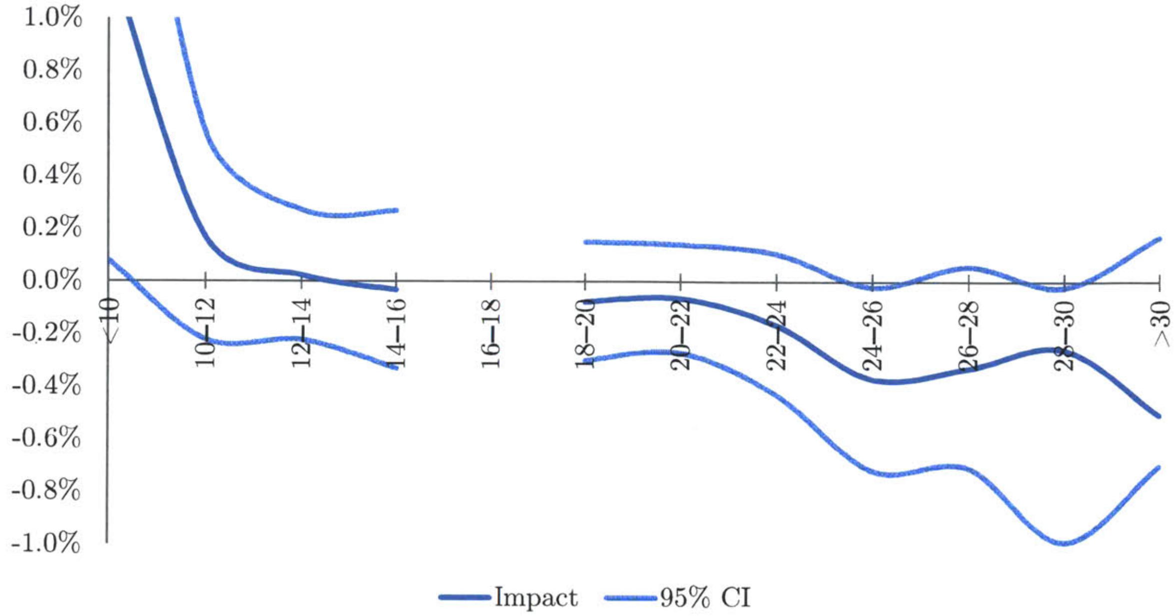

Figure 23. Estimated impact of a growing-season day in 12 temperature ranges on log annual agricultural output, relative to a day in the 16°-18°C range

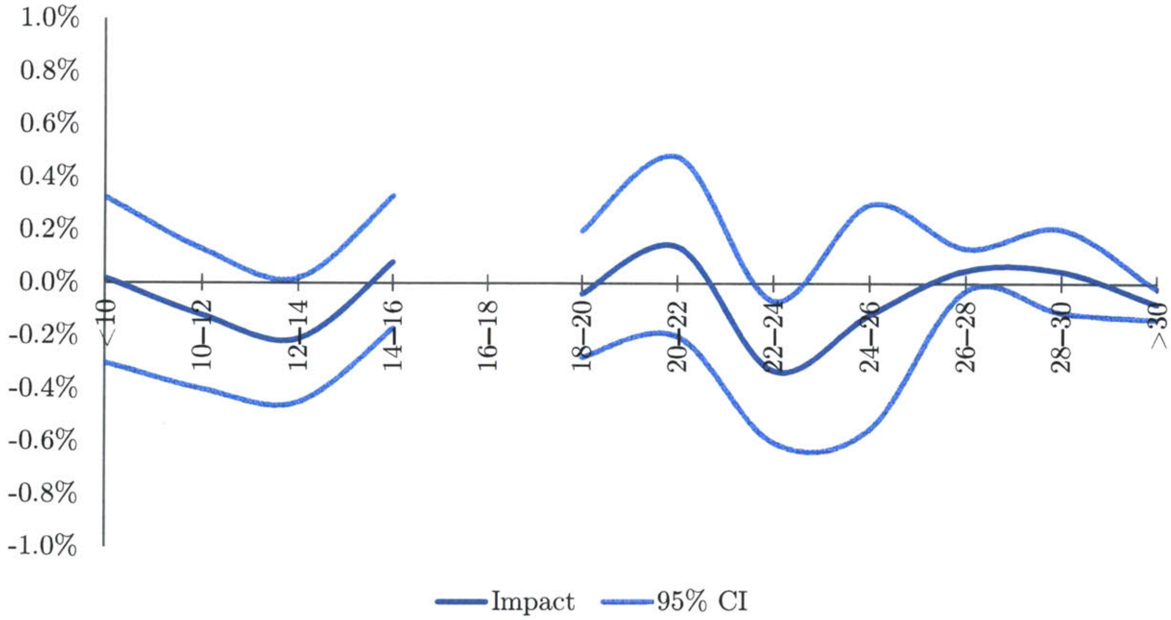

Figure 24. Estimated impact of a non-growing-season day in 12 temperature ranges on log annual agricultural output, relative to a day in the 16°-18°C range

Chapter 2

Weather and the Coming Death of Mexico's Poor: A Regional Analysis of the Cost of Climate Change†

"The rich will find their world to be more expensive, inconvenient, uncomfortable, disrupted and colorless; in general, more unpleasant and unpredictable, perhaps greatly so. The poor will die."

Kirk R. Smith
Symposium on Climate Change
and Health Introduction, 2008

1 Introduction

The decade from 1900 to 1909 was colder than 95% of the last 11,300 years, since the end of the last Ice Age. If not for anthropogenic influences, due to the natural cooling phases of our planet, the Earth would be currently undergoing a cold phase and getting even colder. Contradictorily, the decade from 2000 to 2009 was hotter than about 82% of the last 11,300 years. In fact, temperatures have increased in the last hundred

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years as much as they had cooled in the last seven thousand, a significant feature considering the Holocene period's stable weather patterns. If emissions continue as currently predicted, global temperatures will rise well above anything the world has ever seen since the last deglaciation, more than 11 millennia ago (Marcott et al. 2013.)

This exceptionally dramatic change in climate is in itself one of the most perilous threats to mankind, but in particular one of the most significant welfare risks developing countries face, in particular because most of them are poorly prepared to face it (Andersen et al 2010.) Aside from the many ecological and biophysical implications a changing weather poses worldwide (Walther et al. 2002; Parmesan 2006), climate change, from the public policy standpoint, is a threat to poverty alleviation and economic development: extreme climatic variability, particularly in the context of poverty –when resilience to shocks is already low–, erodes people's assets and their livelihood strategies. The socioeconomic implications of climate change range, *inter alia*, from water scarcity and natural hazards that lead to household and community asset depletion (Rossing 2010; Rossin & Rubin 2010) to severe disruptions in the agricultural production systems and food insecurity (Olesen 2010) to significant human health risks, forced displacement (particularly in coastal areas), and resource scarcities that potentially lead to armed conflict (Nielsen 2010; Andersen et al. 2010; Andersen, Lund & Verner 2010; Rubin 2010.) This process of climate-change-derived inequity—with the rich in general being, until recently, the cause of the problem and the poor in general disproportionately suffering the consequences, is likely to hinder the development process, on the one hand, and exacerbate regional disparities, on the other hand.

In this paper, I argue that climate change is not only an environmental issue, but a welfare, and in particular, a health issue. The purpose of this paper is to provide evidence on the regional welfare impact of climate change in the context of high vulnerability to weather variability. In order to attain this, I study the case of Mexico, a country that, given its socioeconomic conditions and geohydrological characteristics, will be particularly affected by climate change and the extreme-weather thereof derived (United Nations 2011.) The Global Humanitarian Forum (2009) specifically underscores that Mexico is one of the most vulnerable regions to climate change, especially because of floods and increased rainfall variability. Similarly, The World Bank (2009) places

Mexico among the countries most vulnerable to climate change: 68% of its population and 71% of its GDP are at risk of suffering the adverse consequences of this environmental phenomenon. Borja-Vega and De la Fuente (2013) show that climate change will increase agricultural vulnerability, especially in municipalities with more adverse socio-demographic conditions (see Figure 1.) Ethnographic data collected in agricultural communities in rural Mexico have evidenced how constraints in soil quality, topography and water resources make rural regions in Mexico extremely sensitive to climatic conditions (Eakin 2006.)

The remainder of this paper is organized as follows. In Section 1, I introduce the methodological and empirical innovations of my research as well as the contributions to filling existing research gaps. In Section 2, I cover the review of the literature on the future impact of climate change on health and mortality. In Section 3, I introduce the theoretical foundation of the paper, establishing the relationship between short-run weather fluctuations and long-term climate change. In Section 4, I present a detailed description of the data, while in Sections 5 and 6, I discuss the empirical specification I employed to establish the relationship between climate change and mortality and show the results. In Section 7, I conclude with several policy and planning recommendations to build up regional adaptive capacity.

2 Research Gaps and Contributions

The novelty of this paper is that it investigates the climate change issue from both a spatial and vulnerability perspective in Mexico, an industrializing country. The focus of a substantial body of empirical work devoted to this issue has been on Western nations, yet it is in the developing world where vulnerability to climate change is more salient, primarily because agriculture plays a larger role in the economy and access to healthcare is inadequate. In Mexico, empirical studies on the impact of climate change are rare and applied research on the weather-health relationship is even scarcer, plausibly as a result of the exhaustive data requirements such research would entail (Riojas Rodríguez 2006.)

Most of the previous empirical research on the human impact of climate change in Mexico assesses both social and environmental impacts at the national scale and generalizes its findings for the population as a whole. Empirical research on particular subgroups of Mexicans is still nascent and regional analyses are few and constrained and generally observational. Noticeably, there is no single rigorous, non-anecdotal evidence-based analysis assessing the impact of climate change on infants, young children, women, indigenous groups, the elderly, or other groups disproportionately at risk. Similarly, the limited amount of regional projections on changes in temperature and precipitation to assess the vulnerability of the country's population to extreme climate events, as well as of adaptation measures, are mostly based on statistical downscaling methods (Magaña Rueda 2010.) Such techniques are not designed to improve on the modeling of physical processes and feedbacks, so that many of the potential implications of climate change at the regional level in Mexico derived from the employment of these methodologies are inadequate for policy-making instrumentation (Estrada et al. 2012.) High-resolution climate models do a better job simulating climate-change effects.

This paper is a contribution to solving this research gap. I use high-resolution climatic data for all the 2,454 municipalities of Mexico for the period 1980-2010, along with climate predictions from a major coupled atmosphere-ocean general circulation model for the period 2011-2099 to attribute the regional impact of climate change on welfare in Mexico. I study how future climate is expected to affect human welfare in rural and urban areas, as well as the five Mexican mesoregions[14] over the next century, in a (business-as-usual) scenario, where the consumption of fossil fuels does not decrease. In particular, I focus on the serious health risk climate change poses by studying the temperature-mortality dynamics both at the national and subnational scale. I also study how climate change is expected to primarily affect vulnerable subgroups of

[14] Mexico's five mesoregions (Northeast, Northwest, South, Center, and Center-West), as defined in the 2001-2006 National Development Plan, can be considered merely a geographic definition of boundaries which group two or more states into a common territorial delimitation, created for regional development coordination purposes. Given the spatial proximity of states within a given mesoregion, it is fair to say that each mesoregion is fairly homogeneous, at least in terms of climate and geography (see Figure 2.) Indeed, Mexico's mesoregional division and the Köppen climate classification main groups have a fairly consistent overlap.

the population –infants, the elderly and the poor– by predicting age-group-specific and area-specific impacts of climate change. By combining highly detailed mortality time series at the municipal level with high-resolution climate data, this is one of the first large-scale applied works studying the relationship between future climate change and death presenting ideal data conditions for empirical analysis. The World Bank (2010, p. 10) emphasizes that "robust climate change assessments should be undertaken by drawing on long-term (at least 30-year), high-quality records. [...] In practice, such data sets are seldom available."

The climate-change-death relationship is a critical policy and planning issue. As I discussed in Guerrero Compeán (2013), a number of human diseases derive from severe weather and climate extremes, from cardiovascular and respiratory illnesses caused by anomalous hot and cold weather, to the transmission of infectious diseases and malnutrition from crop failures. The World Health Organization (WHO) estimates that the warming and precipitation trends due to anthropogenic climate change claim 150,000 lives every year (Patz, Campbell-Lendrum, Holloway & Foley 2005.) In 2000 alone, 92,000 disability-adjusted life years (DALY), a measure of harm to human health equal to the number of years of life lost due to premature death plus the number of years lived with disability, were attributed to climate change in Latin America, almost twelve times as many as in developed countries (Costello et al. 2009; Campbell-Lendrum, Corvalán & Prüss-Ustün 2003.) The occurrence of climate-change-induced extreme events is likely to increase in the region (Gutiérrez & Espinosa 2010.)

Another innovation of this paper is the methodology it employs to measure climate-change impacts. Most empirical research on the impacts of climate change resorts to either the experimental approach or the Ricardian approach. The experimental approach, usually applied in agricultural economics and biology, relies on controlled experiments where analysts manipulate temperature, greenhouse gases and rainfall levels across crops to see how plant life responds and yields differ. Jentsch, Kreyling and Beierkuhnlein (2007) summarize key findings of experiments manipulating weather events. While this "weather randomization" has the potential to reliably reduce spurious causality, most probably it inaccurately takes into account the adaptive behavior of optimizing farmers, producing bias (Guiteras 2008.) Conversely, the Ricardian approach is based on the assumption that the productive value of land characteristics can be derived from the sale value of land, in which case the implicit prices of characteristics reflect their contribution to productivity in perpetuity, an observation credited to David Ricardo. In the context of climate change, this approach is used to determine the implicit value of climate and its impact on agricultural revenues and productivity (Maddison, Manley & Kurukulasuriya 2007), with its inherent health and, more broadly, welfare implications. Mendelsohn et al. (2000) review the Ricardian approach at length. Like the experimental approach, the Ricardian approach also poses methodological challenges. This technique does better than "weather randomization" in accounting for adaptive behavior by virtue of cross-sectional analysis to isolate the impact of climate in determining agricultural profitability. Even so, for this method to be useful, two preconditions are essential: well-functioning market systems should be present and all factors correlated with climate and influencing productivity, such as farmer and soil quality, should be accounted for in the model. Needless to say, this is at best challenging in data-constrained, incomplete-market developing countries (Guiteras 2008.)

A third approach, which I employ in this paper, is based on panel data analysis and makes use of fluctuations in observed weather to measure the impact of climate on agricultural and health outcomes (Deschênes & Greenstone 2007, 2011; Deschênes & Moretti 2009; Schlenker & Roberts 2009.) Because this is a data-intensive approach, most research where panel data analysis has been carried out has focused on the United States and European cases. Along with the work of Burgess et al. (2011) on India, this paper is one of the first attempts to apply this methodology in a developing country. My empirical strategy, as I will discuss later, is an attempt to capture the full distribution of annual fluctuations in weather, identifying weather parameter estimates from municipality-specific and year-specific deviations in yearly weather from mean climate, under the assumption that weather variability is random. As suggested by Guiteras (2008, p. 11), "the use of district-level data is important to obtain adequate within-year climate variation, thereby distinguishing climate impacts from other national-level yearly shocks." Including municipality fixed effects controls for the average differences across municipalities in any observable or unobservable predictors of log mortality rate, so that, say, demographic, socioeconomic, or clinical impacts will not confound with that of weather.

This methodology has benefits with caveats. In particular, the method relies on municipal and time fixed effect identification strategy, thus controlling any omitted variables that are constant over time and/or particular to one municipality and reducing bias. Likewise, panel data reflect intra-year adjustments such as changes in agricultural or health inputs. However, one should bear in mind that estimates from panel data are unable to reflect longer-term *ex post* adaptive capacity strategies, such as technology adoption, institutional regime change, time preference and market decision adjustments.

3 Health Risks Resulting from Climate Change: A Review of the Literature

In this section, I review the current literature on the relationship between climate and health and how its interaction is expected to evolve as a result of future weather variability. Two bodies of research investigate this interaction: on the one hand, empirical analyses based on observed data and past extreme-weather events, focus on current climate-change-attributed and –anticipated impacts on human health; on the other hand, model simulation studies project the implications of climate variability in terms of future health risks and regional vulnerability.

For a survey on the broader literature on impacts on water, ecosystems, food systems and food security, human settlements, infrastructure, and tourism, see IPCC (2012.)

3.1 The Extreme-Weather Literature and Climate Observational Studies

The extreme-weather literature and climate observational studies are, in terms of impact and policy implications, characteristically bifocal. One focus is the extreme-weather phenomenon itself, and the immediate crisis it creates in terms of impacts on wellbeing and the human system. Another focus is the long-term impact of severe events, which concentrates on the implications of exposure and vulnerability. This body of research underscores the uncertainty derived from climate risks, as well as the adaptation processes to cope with severe weather that most societies only had to deal with it very infrequently and who may have to deal with it much more regularly, posing both institutional and behavioral challenges in terms of climate adaptation.

Studies evaluating impacts and risks of extreme events and abrupt weather variability are inherently impact- and policy-oriented in nature, given that preventing and responding to disasters is often deemed a primary role of the state and, innately, the state is the institutional figure that oversights environmental policy and implements disaster response programs, thus being responsible of evaluating their relief effectiveness in the aftermath of any given weather shock. As pointed out by Eakin (2005), the dominance of economic uncertainty over environmental risk in households' decision making implies a continued role for government intervention to help households adapt to climatic stress.

Climate is becoming more extreme; globally it has become hotter. The 15 hottest years since records began in 1850 have been during the past 15 years: 2010 has been the warmest year yet, followed by 1998, 2005, 2003 and 2002 (NOAA, various years.) One of the consequences of extreme climate, particularly severely hot weather, is an increase in mortality rates, especially among children, the elderly and other vulnerable groups. In Guerrero Compeán (2013), I find evidence that extreme heat increases mortality. More specifically, I show that exchanging one day with a temperature ranging between 16 to 18°C for one day with temperatures higher than 30°C increases the crude mortality rate in 0.15 percentage points. In terms of vulnerable populations, I find that the extreme heat effect on death is significantly more acute in rural regions, leading to increases of up to 0.2 percentage points vis-à-vis a 0.07 point-increase in urban areas. Interestingly, I also find that the timing of climate extremes is relevant: if a weather shock takes place during the agricultural growing season, the effects on mortality are large significant, but not so if such shocks occur during the non-growing season. In similar studies, McMichael et al. (2008) and Baccini et al. (2011) evaluate the relation between daily temperature and mortality in developing and European countries, respectively. Both studies report that higher mortality is observed during extremely hot periods.

Even if death does not take place as a result of severe weather, health conditions may deteriorate and infectious disease rates may rise. Based on a time-series and electrophoretic analyses, Hashizume et al. (2008) and Ahmed et al. (1991) provide evidence that factors associated with high temperatures and extreme precipitation increase the incidence of diarrhea in Bangladesh, primarily among the poor. Extreme precipitation patterns have been shown to cause a geographical shift of malaria epidemic regions by changing breeding sites for vector mosquitoes. Outbreaks of malaria were associated with changes in habitat after the 1991 floods in Costa Rica's Atlantic region (Saenz et al. 1995.) An epidemiological study by Kondo et al. (2002) shows an association between increased transmission of water borne diseases and severe rainfall. The authors find that that the incidence of malaria increased by four to five times over non-disaster periods. Similarly, a periodic lack of precipitation for an extended period of time is associated with higher disease rates. Increasing malaria prevalence is associated with warmer climate in central Ethiopia (Tulu 1996), and with extreme climate variability, partly induced by El Niño/Southern Oscillation, in Colombia, Venezuela, India, Sri Lanka, Kenya and Uganda (Bouma & Dye 1997; Bouma & van der Kaay 1996; Lindblade et al. 1999; Poveda et al. 2001; Yé et al. 2007.) Costa (1993) argues that black fever outbreaks are observed in Brazil after extended periods of drought. Outbreaks of infectious associated with contaminated flood water are investigated by Schmid et al. (2005.) Fritze et al. (2008) argue that extreme weather events are associated with acute traumatic stress and have significant mental implications, particularly on low-income or otherwise more vulnerable populations. Research conducted by Larrance, Anastario and Lawry (2007) and Acierno et al. (2007) in communities effected by Hurricanes Charley, Frances, Ivan, Katrina, and Jeanne shows high rates of post-traumatic stress disorder, depression, domestic violence and significantly higher rates of suicide completion and attempts. For a summary of the global burden of climate-change-attributable disease, see Patz et al. (2005.)

Another outcome of extreme climate is crop damage, which indirectly affects human health through its impact on food security. Health outcomes are negatively influenced as a result of adverse weather disrupting the household's sources of income on which it relies for subsistence (Burgess et al. 2011.) Indeed, many regions in the world, and particularly the poorest, rely almost solely on small-scale, climate-sensitive subsistence farming, which is especially susceptible to inclement weather (IPCC 2012.) Sen (1981, p. 449) discusses the association between that the Ethiopian and Bangladeshi famines of the early 1970s and weather (droughts and floods, respectively), and points out that in both cases farmers where disproportionally affected. Similarly, consumption of basic goods and food intake is restrained as a result of natural-calamity-induced supply shortages, speculative behavior, and increased demand to deal with uncertainty. The economic consequence of extreme weather is thus higher food prices, which ultimately affect the poor as a result of reduced purchasing power, thus increasing their likelihood of becoming famine victims (Lin & Yang 2000.) Sen (1981) discusses that the wages paid to farm laborers in 1942 did not keep up with the rising price of food, which was caused, *inter alia*, by a hurricane that affected rice harvests, as well as inflation in Calcutta, which was triggered by the Raj putting money into war production. This resulted in farmers suffering a reduction in their ability to command power over food, which eventually resulted in the Bengal famine of 1943. Similar cases in Africa and Europe are discussed at length by Drèze and Sen (1989.) Overall, weather has played a major role in 17 out of 24 major famines from 1693 through 2005 (for a listing of famines, see Ó Gráda (2007, p. 20)), suggesting that food-security is a relevant in terms of human physiology.

Furthermore, the higher temperatures that have been observed in the past years have increased the risk of wildfires. Gillett et al. (2004) employ a coupled climate model to demonstrate that human emissions of greenhouse gases have made a detectable contribution to warmer temperatures, having a detectable influence on the area burned by forest fire in Canada over recent decades. Westerling et al. (2006) attribute the increase in western U.S. forest wildfires to warmer spring and summer temperatures, reduced precipitation associated with warmer temperatures, reduced snowpack and earlier spring snowmelts, and longer, drier summer fire seasons in some middle and upper elevation forests. In addition to the environmental and economic consequences of wildfires, the World Health Organization (1999) finds that major fires in 1997 in south-east

Asia and the Americas are associated with increases in respiratory and eye symptoms. In Malaysia, a two to threefold increase in outpatient visits for respiratory diseases and 14% decrease in lung function in school children was reported. Indirect food security (and consequently, health) impacts of wildfires range from loss of vegetation to a proliferation of eroded fertile soils (Githeko & Woodward 2003.)

Expectedly, a critical issue in the extreme-weather literature is how researchers tie extreme weather and observed climate variability to anthropogenic climate change. In fact, climate change detection can be addressed only as a statistical problem, whereby probabilistic statements are made as to the most likely causes of recently observed climate change. It will never be possible to prove all the causes of recently observed climate change since the Earth's climate system is highly complex (Thorne 2001.) However, despite the impossibility to attribute particular extreme-weather eventualities to anthropogenic climate change, it is possible to establish whether meteorological phenomena fit the more general pattern toward more extreme weather, and in doing so it can be determined whether this pattern can be attributed to climate change, rather than natural processes.

Along these lines, Muller et al. (2012) use sophisticated statistical methods which allowed the determination of earth land temperature since 1753 and the isolation of potential sources of bias raised by climate-change skeptics.[15] They show that the historic temperature pattern and recent climate volatility is best fitted by the record of atmospheric carbon dioxide and its magnitude is consistent with the calculated greenhouse effect. Hansen, Sato and Ruedy (2012) examine how global summertime temperatures have been changing in recent decades. The authors detect that during the period from 1951-1980, extremely hot summers covered just 1 percent of Earth's land area. This rises to 10 percent of the Earth's land area by the period from 1981-2010, and

[15] The authors demonstrate that neither urban heating issues (their results using rural data alone were comparable), nor data selection issues (prior studies selected fewer than 20 percent of the available temperature stations; the authors used virtually 100 percent), or poor station quality issues (the authors separately analyzed good stations and poor ones), nor human intervention and data adjustment issues (the authors' work is automated and hands-off) are potentially problematic and cannot bias their findings. Likewise, the time series is long enough that the authors were able to account for the fingerprint of solar variability, based on the historical record of sunspots, and find that solar variation does not seem to impact the temperature trend.

even higher during the 2006-2010 period. In other words, the odds of such extreme summers were about 1-in-300 during the 1951-1980 timeframe, but that had increased to nearly 1-in-10 by 1981-2010. Such a shift is in probability terms extremely implausible in the absence of climate change. Similarly, Stott, Stone and Allen (2004) investigate the extent to which the 2003 European heat wave was caused by a modification of the external influences on climate. Although natural variability played a role, the authors estimate that it is very likely (confidence level >90%) that human influence had more than doubled the risk of European mean summer temperatures as hot as 2003, and with the likelihood of such events projected to increase 100-fold over the next four decades. Similarly, Tett et al. (2002) investigate the climatic changes as a response to natural and man-made factors using a coupled atmosphere/ocean general circulation model. They find that post-1950 global warming is explained primarily by anthropogenic elements and to a minimum extent by natural variation. Hegerl et al. (1996), North and Stevens (1998), Tett et al. (1999) and Stott et al. (2001) use an optimal detection algorithm to investigate the causes of recent climate change. All of these studies consistently conclude that anthropogenic changes in greenhouse gases have been responsible for the warming observed over the last 50 years.

From a political standpoint, some analysts have studied the link between climate change and conflict. Burke et al. (2009) document strong historical linkages between temperature and civil conflict in Africa, with warmer years leading to significant increases in the likelihood of war. When combined with climate model projections of future temperature trends, the authors project a roughly 60% increase in armed conflict incidence by 2030, or an additional 390,000 battle deaths if future wars are as deadly as recent wars. The climate-conflict relationship has been observed for example in Darfur. The 2007 United Nations Environment Programme Annual Report (UNEP 2007) points out that regional climate change, water scarcity, desertification and deforestation have increased migration flows from Northern to Southern Sudan, and thus might have contributed to the initiation of the conflict (Costello et al. 2009.)

3.2 Future Climate-Change Modelling and Potential-Effect Literature

Given the current impact of a changing and more severe weather and the prospect of climate extremes occurring more often, recent research has attempted to assess the extent to which future climate will affect societies. Despite the limits of climate science (Carmin, Nadkarni & Rhie 2012), the use of climate models and potential trend analyses has become increasingly relevant as the incidence of extreme climatic events is more recurrent (Eakin 2005.) This literature is relatively small, given that accurately assessing the impact of climate change is not simple as a result of the uncertainty and variety of often conflicting assumptions surrounding future human behavior that may have an impact on climate. However, it offers an intellectual platform for decision-makers to prioritize policies for social adaptation to climate change and assess the likely magnitude of the health impacts of severe weather. In words of Campbell-Lendrum, Corvalán and Prüss-Ustün (2003, p. 133), "given the importance of natural climate variability and the potential for societal and individual factors to mediate the potential effects of climate change, only approximate indications of likely impacts can be expected. However, it is important to make such estimates available to policymakers, along with a realistic representation of the associated uncertainty; or remain in the current unsatisfactory condition of introducing a potentially important and irreversible health hazard throughout the globe, without any quantitative risk assessment."

In general terms, according to the IPCC (2012, p. 13) "it is virtually certain that increases in the frequency and magnitude of warm daily temperature extremes and decreases in cold extremes will occur in the 21st century at the global scale. It is very likely that the length, frequency, and/or intensity of warm spells or heat waves will increase over most land areas. Based on the A1B and A2 emissions scenarios, a 1-in-20 year hottest day is likely to become a 1-in-2 year event by the end of the 21st century in most regions, except in the high latitudes of the Northern Hemisphere, where it is likely to become a 1-in-5 year event. Under the B1 scenario, a 1-in-20 year event would likely become a 1-in-5 year event (and a 1-in-10 year event in Northern Hemisphere high latitudes.) The 1-in-20 year extreme daily maximum temperature (i.e., a value that was exceeded on average only once during the period 1981–2000) will likely increase by about 1°C to 3°C by the mid-21st century and by about 2°C to 5°C by the late 21st century, depending on the region and emissions scenario (based on the B1, A1B, and A2 scenarios.) It is likely that the frequency of heavy precipitation or the proportion of total rainfall from heavy falls will increase in the 21st century over many areas of the globe. This is particularly the case in the high latitudes and tropical regions, and in winter in the northern mid-latitudes. Heavy rainfalls associated with tropical cyclones are likely to increase with continued warming. There is medium confidence that, in some regions, increases in heavy precipitation will occur despite projected decreases in total precipitation in those regions. Based on a range of emissions scenarios (B1, A1B, A2), a 1-in-20 year annual maximum daily precipitation amount is likely to become a 1-in-5 to 1-in-15 year event by the end of the 21st century in many regions, and in most regions the higher emissions scenarios (A1B and A2) lead to a stronger projected decrease in return period."[16] However, Rahmstorf (2007), Hansen et al. (2007), O'Gorman (2012), Fasullo and Trenberth (2012), Muller et al. (forthcoming) and other studies have raised the concern that these estimates are overly conservative and climate change may in fact be more severe.

The potential health effects of such a change in climate, even by the most conservative estimates, are significant. Overall, the literature emphasizes at least four channels through which climate variability affects health outcomes: propagation of dis-

[16] A number of greenhouse gas emissions scenarios are described in the IPCC Fourth Assessment Report (2007.) They have been used to make projections of possible future climate change. The A1 family of scenarios is characterized by rapid economic growth, a global population that reaches 9 billion in 2050 and then gradually declines, the quick spread of new and efficient technologies, and a convergent world, where income converges between regions and extensive social and cultural interactions worldwide occur. There are subsets to the A1 family based on their technological emphasis. The A1FI scenario emphasizes fossil-fuel use; Scenario A1B assumes a balanced emphasis on all energy sources; Scenario A1T - Emphasis presumes a non-fossil energy-intensive world. Similarly, the A2 family of scenarios is characterized by a world of independently operating, self-reliant nations, with continuously increasing population and regionally oriented economic development. Conversely, the B scenarios are of a more ecologically friendly world. The B1 scenarios are characterized by rapid economic growth as in A1, but with rapid changes towards a service and information economy, population rising to 9 billion in 2050 and then declining as in A1, reductions in material intensity and the introduction of clean and resource efficient technologies, and an emphasis on global solutions to economic, social and environmental stability. Finally, the B2 scenarios are characterized by a continuously increasing population, but at a slower rate than in A2, an emphasis on local, rather than global, solutions to economic, social and environmental stability, intermediate levels of economic development, and less rapid and more fragmented technological change than in A1 and B1.

eases (infectious and otherwise), extreme temperatures, an increased incidence of natural disasters, including floods and droughts, and higher levels of pollution (Haines & Patz 2004.)

Hijoka et al. (2002) find that, even though climate change will have some benefits in terms of health, primarily in the form of decreased mortality rates and increased agricultural yields in temperate regions, these are overwhelmingly outweighed by significant increases in diarrhea, cardiovascular diseases, higher mortality rates in coastal regions and malnutrition. Assuming unmitigated emissions, Campbell-Lendrum, Corvalán and Prüss-Ustün (2003) project an increase in the burden of diarrheal diseases in low-income regions ranging from 2 to 5% in 2020. Hales et al. (2002) conclude that, by 2085, climate change will put 5-6 billion people at risk of dengue, compared to 3.4 billion people if the climate remained unchanged. Climate change will cause a spatial expansion of the areas suitable for malaria in some regions, predominantly in Africa. Tanser, Sharp and Le Sueur (2003) provide evidence that, by 2100, Africa can expect a 16 to 28% increase in person-months of malaria exposure across all IPCC emissions scenarios. Using data for Zimbabwe and India, respectively, Ebi et al. (2005) show that mountainous areas will become more suitable for transmission, while Bhattacharya et al. (2006) find that the malaria transmission window is likely to widen in more temperate regions. Globally, Lindsay and Martens (1998) project that at least 260 million more people will be exposed to malaria by 2080 due to new endemic disease transmission areas. Other studies conclude that higher-latitude countries will be exposed to Lyme disease and tick-borne encephalitis by the 2050s if climate change is not mitigated (Ogden et al. 2006; Randolph & Rogers 2000.) Likewise, schistosomiasis, fascioliasis, echinococcosis, leishmaniasis, and hantavirus infections are expected to increase as a result of a changing weather (Mas-Coma, Valero & Bargues 2008; Cárdenas et al. 2008; Gray et al. 2009; Clement et al. 2009.)

Other studies investigate the association between expected future warmer temperatures and mortality. As I show in Guerrero Compeán (2013), heat mortality follows a *J*-shaped function with a steeper slope at higher temperatures, so it is anticipated that global warming will increase mortality rates at a worldwide scale. Using an empirical model derived from observed mortality, Donaldson et al. (2001) find that annual heat-related deaths in the United Kingdom more than quadruple from 798 in 1990s to 3,519 in the 2080s under a medium-high warming scenario and, conversely, they show that cold-related deaths decrease from 80,313 to 51,243 over the same time period. In a similar work, McMichael et al. (2003) find that the temperature-attributable mortality rate in Australian major cities will triple at the end of the 21^{st} century assuming a 0.8-5.5°C increase in annual maximum temperature. Burgess et al. (2011) estimate an increase in the overall Indian annual mortality rate of approximately 12% to 46% by the end of the century. The estimated increase in rural areas ranges between 21% and 62%. A similar exercise performed on the United States by Deschênes and Greenstone (2011) suggests that, under a "business as usual" scenario, climate change will lead to a roughly 2% increase in the overall mortality rate there by the end of the century. A typical critique of these works is that they do not assume acclimatization, that is, these models ignore the possibility of people adapting to new climate conditions. Because of economic, technological, and physiological reasons, one would expect societies to adapt to an anticipated and slowly warming climate in various ways. However, rather than dismissing the conclusions of these studies, their findings should be viewed as upper bound estimates of the impact of climate change. Studies that do account for adaptation present similar conclusions. Koppe (2005) finds a 20% increase in heat-related mortality in Baden-Württemberg, Germany between 1951-2000 and 2001-2055, assuming an A1B emissions scenario. The author also shows that this increase will not be compensated by reductions in cold-related mortality. Likewise, in a study for Lisbon, Portugal, Dessai (2003) finds an increase in heat-related mortality rate from 5.4 to 6 deaths/100,000 in the 1968-1998 period to 19.5 to 248.4 deaths/100,000 by the 2080s. As a result of increased temperature and decreased precipitation under climate change, Butt et al. (2005) project that the percentage of the population of Mali at risk of hunger will increase from 34% at present to 64-72% by mid-21^{st} century.

The extent to which climate change may cause more natural disasters has also been at the center of recent empirical research. Combining models that predict broad climate changes decades into the future with those that simulate storm development, Lin et al. (2012) project that climate change could lead to floods that should occur only once a century happening every three to 20 years, while a 500-year surge could happen every 25 to 240 years. Battisti and Naylor (2009) find that in tropical and sub-tropical areas future growing-season temperatures are expected to exceed the most extreme temperatures observed from 1900 to 2006, with substantial potential implications for food systems around the world. Ranger et al. (2011) provide evidence that loses resulting from once-in-a-century flood events in Mumbai, India are likely to triple between now and the 2080s, increasing from 700 million to 2.3 billion USD. Based on mid-range sea-level rise estimates, Manuel (2006) estimates that the New Orleans region will be up to four meters below sea level by 2100. Likewise, Carmin, Anguelovski and Roberts (2012) document that sea levels in Durban, South Africa are rising, on average, by approximately 3cm each decade, and pose a threat to urban residents in terms of water scarcity, infrastructure damage, and a variety of public health issues.

Pollution has also been the focus of climate-change-impact research. Depending on the set of assumptions regarding population dynamics, economic growth, and environmental regulation, this body of research attempts to determine how potential changes in concentrations of pollutants, mainly ozone may impact future morbidity and mortality. Using a concentration response function, Knowlton et al. (2004) find that ozone-related deaths will increase roughly 5% by the 2050s in the New York metropolitan area. Their findings assume a population and age structure constant at year 2000, no changes in the United States Environmental Protection Agency 1997 national emissions inventory, and increases in volatile organic compounds and oxides of nitrogen consistent with a A2 emissions scenario. Following a similar methodology and assumptions for 50 Eastern United States cities, Bell et al. (2007) find that ozone-related deaths will increase roughly 0.3% by mid-21st century. Mickley et al. (2004) project increases in the severity and duration of summertime regional air pollution in the Northeast and Midwest United States by mid-21st century as a result of climate change.

3.3 Evidence from Mexico

Research has repeatedly shown that Mexico is very sensitive to climate change (O'Brien & Leichenko 2000.) Aguilar et al. (2005) show that changes in temperature extremes over the 1961–2003 period indicate warming for Mexico and Central America.

The authors show that temperatures are increasing at a decadal rate of roughly 0.2°C. A similar rate is found in SEMARNAT (2009.) Compared to the rest of the world, Mexico will experience above-average warming, with medium-risk scenarios predicting, on average, 0–2°C rises by 2020, 1–3°C rises by 2050, and 2–4°C rises by 2080 (SEMARNAT 2009.) This is consistent with the findings of Liverman and O'Brien (1991), who study several general circulation models and project changes in temperature ranging from 2.3 to 5.4°C by the end of the century. Other studies project worse scenarios, with 0–3°C rises by 2020 and up to 4–8°C rises by 2050 (Tejeda Martínez, Conde Álvarez & Valencia Treviso 2008.) Furthermore, precipitation patterns are expected to become more extreme as a result of climate change, with dry regions experiencing more droughts and wet regions facing more floods (Magaña & Caetano 2007.) Meteorological data from Mexico's National Meteorological Service show that, even though there is no indication of an increase in intensity in Mexico, 28 hurricanes hit between 1970 and 1989, while 42 struck between 1990 and 2010 – a 50% increase (Comisión Nacional del Agua 2012.) Sea levels are projected to rise 18-59cm by 2090-2099, with the respect to the baseline period 1980-1999 (IPCC 2007.)

In terms of health, the Ministry of the Environment of Mexico projects a "substantially higher" incidence of dengue, malaria, and gastrointestinal diseases as a result of climate change (SEMARNAT 2009.) Depending on the region, a 1°C-increase in temperature is associated with up to a 1% increase in deaths attributed to these diseases (Riojas Rodríguez 2006.) However, based on a more focalized retrospective ecological study, using data from two municipalities in the state of Veracruz, Hurtado Díaz et al. (2007) document that a 1°C-increase in temperature is associated with more than 40%-increases in the number of dengue cases after four to five months. Similarly, Colón González, Lake and Bentham (2011) show that the incidence rate of dengue is positively associated with the strength of extreme-weather events, with the risk of infection being higher during El Niño conditions.

Conde and Gay (1999) identify the Central and Northern parts of the country and the coastal region in Tabasco as the most weather-vulnerable parts of Mexico. The areas in the north and those with large populations, particularly in central Mexico, are more vulnerable to drought and desertification, due to erosion and the increasing drought resulting from high temperatures and variations in precipitations in these arid and semi-arid regions. In turn, the coast of the state of Tabasco will be more vulnerable to changes in sea levels. Estimates suggest that the sea could reach between 40 and 50 kilometers inland. These phenomena have important health consequences, ranging from malnutrition to higher incidence of diseases to water pollution. Although vector-borne diseases will expand their reach and death tolls as a result of more recurrent heat waves, especially among elderly people, the indirect effects of climate change on water, food security, vulnerable shelter and human settlements, and extreme climatic events are likely to have the biggest effect on health (Costello et al. 2009.) Using an autoregressive integrated moving average model in a study for the National Institute of Public Health of Mexico, Riojas Rodríguez et al. (2007) find that extreme weather patterns in the Olmec region are associated with a significantly higher incidence of gastrointestinal diseases and respiratory infections. A national study carried out by the same agency (Riojas Rodríguez et al. 2008) finds that a 1-centigrade temperature increase is expected to increase both gastrointestinal disease and dengue rates by 4-5% by 2030.

From an economic standpoint, Borja-Vega and De la Fuente (2013) show that climate change will increase agricultural vulnerability in Mexico, especially in municipalities with more adverse socio-demographic conditions. Although their analysis suggests a wide variation in municipal vulnerability, they provide evidence that the Northwest and Central regions will experience significant increases in vulnerability between 2005 and 2045. Galindo (2009) finds that the consequences of climate change for Mexico vary widely between regions and while many regions are likely to be negatively affected, there could even be temporary gains in some of these. However, in the long term, the negative economic effects surpass temporary gains. By 2100, the total economic costs of climate change, according to his calculations, would be equivalent to an accumulated loss of between 6% and 30% of Mexico's GDP, although the uncertainty associated with these calculations has to be taken into account. One of the sectors in which major losses would occur is that of agriculture and livestock farming, so the rural population would be most affected (Albo & Ordaz Díaz 2011, Liverman 1999.) Corn's phonological cycle may be reduced by as much as 13% by 2080 as a consequence of future warmer temperatures, which would diminish the plant's ability for nutrient absorption (Ojeda, Martínez & Hernández 2006; Prieto et al. 2007.) Other climate-change-induced ecosystem impacts, including deforestation, biodiversity losses and extensive plague exposure, as well as economic impacts in the tourism, energy and infrastructure sectors, are discussed in SEMARNAT (2009.) As I discuss in Guerrero Compeán (2013), the economic impacts in these activities and population groups in particular translate directly into higher morbidity and mortality rates.

4 General Conceptual Framework for the Methodological Approach

The theoretical foundation of this paper is based on Guiteras's (2008) model of farmer output and Rosenzweig and Schultz's (1983) household production of health model. Let the production of health by the household be $H = f(T, \Gamma, \Theta)$, where T represents temperature, Γ represents health inputs that can vary in the short term, such as healthy lifestyle choices, avoidance of injury, sanitary and nutrition habits and healthcare utilization, and Θ represents inputs that are fixed in the short term and may only be adjusted in the long term or not even be in the household's control at all, like migration decisions, health technology, medical research and development, and environmental quality, standards, and regulation. If temperature and prices are taken as given, the household maximizes utility by

$$max\{p \cdot f(T, \Gamma, \Theta\} - p_\gamma \Gamma - p_\theta \Theta \tag{1}$$

where p_γ and p_θ are the costs of short- and long-term health inputs, respectively, which are assumed to be linear for simplicity. If inputs are not fixed, at the temperature T, the household maximizes utility by choosing $\Gamma(T)$ and $\Theta(T)$, obtaining as a result an utility of $\pi(T, \Gamma(T), \Theta(T))$. This is the hypothetical case of full adaptation by the household.

If climate changes and temperature increases but households have their health inputs fixed, in the representative case, maximized utility would be $\pi(T', \Gamma(T), \Theta(T))$. This situation is best characterized by either the experimental or Ricardian approaches discussed in the introduction. These models do poorly in terms of accounting for adaptive behavior due to their assumptions and data requirements (Guiteras 2008.) By virtue of these types of models understating the possibility of adaptation, the effect of climate change on the utility of the household would be

$$\widehat{\Delta\pi_R} = \pi(T', \Gamma(T), \Theta(T)) - \pi(T, \Gamma(T), \Theta(T)) \tag{2}$$

If households can reoptimize Γ, but are constrained from adjusting Θ, that is, if families can adapt their short-term health inputs, but are constrained from changes in long-term health inputs, the utility of the household after a change in climate would be $\pi(T', \Gamma(T'), \Theta(T))$. In this case, the effect of climate change on the utility of the household would be

$$\widehat{\Delta\pi_P} = \pi(T', \Gamma(T'), \Theta(T)) - \pi(T, \Gamma(T), \Theta(T)) \tag{3}$$

This situation is best characterized by panel data analyses. This method can reflect intra-year (i.e., short-term) adjustments in agricultural or health inputs resulting from climate variation. However, estimates from panel data are unable to reflect (longer-term) *ex post* adaptive capacity strategies, such as technology adoption, institutional regime change, time preference and market decision adjustments.

If, given climate change, households could adjust all health inputs, the utility in the representative case would be $(T', \Gamma(T'), \Theta(T'))$. Because households can reoptimize all their health inputs, one can assess the true impact of climate change, which equals

$$\widehat{\Delta\pi} = \pi(T', \Gamma(T'), \Theta(T')) - \pi(T, \Gamma(T), \Theta(T)) \tag{4}$$

Assume that households have complete and transitive preferences and exhibit monotonicity in the sense that more choices increase utility. This means that a utility function $u: \mathbb{R}_+^n \to \mathbb{R}_+$ is strictly monotone if $\forall x, y \in \mathbb{R}_+^n, x \geq y \Rightarrow u(x) \geq u(y)$. Hence, the following result is generated:

$$\widehat{\Delta\pi} > \widehat{\Delta\pi_P} > \widehat{\Delta\pi_R} \tag{5}$$

Methodologically, panel-data models provide a better approximation than the Ricardian approach to the true impact of climate change, given that such models partially account for adaptive behavior (see Figure 3.) Given that panel-data models are able to reflect intra-year year (i.e., short-term) adjustments, they can do reasonably well if changes in climate are small or in a situation where households carry out long-term health input adjustments gradually. Drastic climatic changes, however, will result in panel data models overestimating the impact of climate change relative to the true long-term impact, when households have adapted (Guiteras 2008.)

As documented in the literature, households, especially the poor ones, are anticipated to adapt slowly to a changing climate. Guiteras (2007) cites three reasons. First, it is difficult for households to assess whether climate patterns are changing based solely on year-to-year extreme events (IPCC 2007.) Realizing the need to adapt to a warmer climate through the reoptimization of health and other inputs may take time as a result. Second, carrying out changes in long-term health inputs may be costly for households (i.e., the decision to migrate involves large fixed costs and irreversible processes), so that input reoptimization may be deferred, especially in the presence of uncertainty (Bertolla & Caballero 1994; Dixit & Pindyck 1994.) Third, asymmetric information, low human development, hyperbolic time preferences, and failures in the credit and insurance markets (which are common in developing countries), hinder the process of adaptation (Foster & Rosenzweig 1995; Duflo, Kremer & Robinson 2009.)

5 Data Construction

An empirical specification of the theoretical framework presented above, which illustrates the human impact of weather, requires data on three types of variables: one that operationalizes human health, one that operationalizes current climate patterns, and one that operationalizes future climate changes.

Typical variables that may work well to assess the impact of weather variation on human health include the incidence of particular water- and vector-borne diseases, hospital admissions, clinic attendance, morbidity rates, and mortality rates (WHO, WMO & UNEP 2003.) Similarly, the natural choices for studying climatic phenomena are temperature, pressure, rainfall, hail, aridity, wind, as well as the occurrence of certain weather events like tornados and cyclones (WMO 2012.)

As good evidence requires good data, I select those variables generated with high frequency, high spatial disaggregation, and high-quality monitoring. The following constitute the variables that will be employed for the empirical analysis that I will carry out in the next section.

5.1 Mortality

The ultimate health impact of severe weather is death. Vital statistics, given their high disaggregation and frequency, are of particularly good quality in Mexico. To calculate mortality rates, information on deaths, births, and population are needed. I obtain death and birth counts data at the municipal level through each state's Civil Registry Office. Since each state has its own registration data and formats, I digitize and harmonize the 32 datasets (31 state datasets and one dataset for Mexico City) using standardized codes for births, deaths, and fetal deaths. I collect monthly data for the period January 1990-December 2010 for 2,454 Mexican municipalities (99.9% of the total.)

Given that annual population data are not available for Mexican municipalities, I construct a population monthly time series using censal information for population in combination with migration flow data obtained from Mexico's National Council of Population Demographic Indicators and the State and Municipal Database System of

Mexico's National Institute of Statistics (INEGI.) These data are available for years 1990, 1995, 2000 and 2010. For intercensal years, I estimate (midyear) population using the component method, which is defined simply by the use of estimates or projections of births, deaths, and net migration to update a population (Hollmann, Mulder & Kallan 2000.) In its simplest statement, the component method is expressed by the following equation:

$$P_t = P_{t-1} + B_{t-1,t} - D_{t-1,t} + M_{t-1,t} \tag{6}$$

where P_t = population at time t;
P_{t-1} = population at time $t-1$;
$B_{t-1,t}$ = births, in the interval from time $t-1$ to time t;
$D_{t-1,t}$ = deaths, in the interval from time $t-1$ to time t; and
$M_{t-1,t}$ = net migration, in the interval from time $t-1$ to time t.

For simplicity, I compute intercensal net migration using what demographers refer to as the Das Gupta method (Das Gupta 1991.) This technique assumes that the ratio of the intercensal estimate to the postcensal estimate should follow a geometric progression over the lustrum. Naturally, there is no universal norm for producing intercensal migration estimates, and other methodologies could have also been employed.

With these variables, I construct a crude (total) mortality rate, which I define as the total number of deaths (excluding fetal deaths) per period per 100,000 people. In addition to the crude mortality rate, I also distinguish among two subtypes of mortality indicators: child or "early-life" mortality rate (i.e., the number of deaths of children less than 5 year old per period per 100,000 people); and "late-life" mortality rate (i.e., the number of deaths of people aged over 70 per period per 100,000 people.) These are important given that children and seniors are more vulnerable than other population groups to injury, disease, and other negative impacts resulting from climate change (IPCC 2007; UNICEF 2011.) I also compare these mortality rates by age group and type of area, defining rural mortality rate as the mortality rate in communities with fewer than 2,500 residents, and urban mortality rate as the mortality rate in communities with 2,500 residents or more. Tables 1 and 2 present relevant descriptive statistics.

The comparative analysis of urban and rural areas is of particular relevance. The distinction follows an intuitive logic: climate change is more likely to impact rural communities. On the one hand, extreme weather has a clear and direct impact on agriculture, and this sector is the main source of employment for rural regions. The latest Household Income and Expenditures National Survey (INEGI 2011) is indicative: in 2010, almost 62% of surveyed households living in rural communities worked in the agricultural sector, while only 7% of households residing in urban areas did. On the other hand, this spatial imbalance translates into significant differences in income: the same survey reports that, also in 2010, households where no members were employed in agriculture had an income, on average, of 13,365 Mexican pesos per month (1,062 USD.)[17] Households with some (but not all) members being employed in the primary sector of the economy, earned, on average, 8,618 pesos (686 USD.) Finally, in the case where the entire household is engaged in agricultural work, monthly income averages 4,841 pesos (385 USD), or roughly a third of income in non-agricultural households.

These differences are reflected in two different patterns of household consumption: monthly expenditures in urban areas are high (relative to rural communities) and food consumption has a relatively smaller share of total expenditures. Urban households spend on average 8,878 pesos (707 USD) per month, of which almost 32% is spent on food. In contrast, rural households spend on average 4,602 (366 USD) pesos per month, of which 40% is spent on food.

5.2 Years of Life Lost

A useful measure that is alternative to mortality rates is the years of life lost. This indicator takes into account the age at which deaths occur by giving greater weight to deaths at younger age and lower weight to deaths at older age, thus providing an indi-

[17] Based on the average midpoint exchange rate of 0.0796 MXN/USD from August 21, 2010 through November 28, 2010, the period when the survey was carried out.

rect measure of the opportunity cost of premature mortality, given age at death. A rather crude approach to calculating the years of life lost for a given cause, given sex or age, is $YLL = n_d \cdot e^s_x$, where YLL is the number of years of life lost, n_d is the number of deaths and e^s_x is the standard life expectancy at age of death (in years.)

In order to calculate YLL, analysts usually resort to model life tables. A life table is a concise way of showing the probabilities of a member of a particular population living to or dying at a particular age. In general, such life tables include, for a given set of age intervals, estimates of life expectancy, age at death, probability of dying, and the estimated number of individuals surviving past a given age, among other metrics. Two sets of standard model life table families (Coale & Demeny 1966; United Nations, 1981) are commonly used to derive a variety of mortality indicators and as underlying mortality patterns for estimation and projection by the demographic research community at large.

I construct a period life table for Mexico based on Coale and Demeny (1966) regional model life tables (see Table 10), assuming a life expectancy of 75 years (for the period 1990-2012, the life expectancy average was 73.7 years (INEGI 2012a.)) I employ an extension set of the Coale and Demeny model life tables, which corrects for substantial deviation for out-of-sample predictions. Tabulations including age-specific mortality rates, probabilities of dying, survival level and ratios, by sex and level of life expectancy were computed by the United Nations Population Division (Li & Gerland 2011; UNPD 2012.) I combine Coale-Demeny life expectancy patterns for males and females into age-range-specific pooled patterns by taking a weighted average of the age-range-specific patterns, where the weights are the average censual population of males and females over the 1990-2010 period.

I obtain censual population statistics, by sex and age group, from the National Institute of Statistics, Geography and Informatics of Mexico (INEGI)'s Censual Historic Series. These data are available for years 1990, 1995, 2000 and 2010 (INEGI 2012b.) In addition, I obtain age-at-death statistics from INEGI's Administrative Registers Statistics Multi-Screen Data-Search System (INEGI 2012c.) Age-at-death data are available for the 1990-2011 period.

Several studies make use of the basic $YLL = n_d \cdot e_x^s$ metric to estimate the number of years of life lost (an example that is related to the subject of this paper is Deschênes and Greenstone (2011.)) Nevertheless, such an approach assumes that a year of life now is equivalent to society to a year of life gained sometime in the future. Similarly, it assumes that lost years of life have equal value regardless of age. Finally, it assumes that for a given age, all individuals lose the same amount of health through death, ignoring the fact that current life expectancies vary between population groups (Prüss-Üstün et al. 2003.) These assumptions are problematic. A number of studies indicate that there is a broad social preference to value a year lived by a young adult more highly than a year lived by a young child, or lived at older ages (Institute of Medicine 1986.) Likewise, people generally prefer a healthy year of life immediately, rather than in the future, if given the choice.

For this reason, rather than computing the basic formulation of YLL, I estimate the net present value of YLL, applying a 3% discount rate to years of life lost in the future, the typical value employed in the demographics and epidemiology literature (Gold et al. 1996.) In addition, I employ a function to model relative age weights, giving more relative weight to lower age values (Murray & Acharya 1997.) Given that both age-weighting and discounting are applied, I estimate the years of life lost by computing

$$YLL = \frac{KC(\exp(ra))}{(r+\beta)^2}\{\exp(-(r+\beta)(e_x^s + x))[-(r+\beta)(e_x^s + x) - 1] - \exp(-(r + \beta)x)[-(r+\beta)x - 1]\} + \frac{1-K}{r}(1 - \exp(-re_x^s))$$

where YLL is the number of years of life lost; x is the age of death (in years); r is the discount rate (usually 3%); e_x^s is the standard life expectancy at age of death x; β is an age-weighting constant (typically 0.04), K is an age-weighting modulation constant (normally 1), and C is an adjustment constant for age-weights, whose value is set at 0.1658 in the World Health Organization's methodology and assessments of Global Burden of Disease (WHO 2012.)

5.3 Observed Weather

The most essential data to carry out any empirical analysis on weather and its impacts are, of necessity, climatic records. There is a variety of models that provide environmental analysts with climatic observations and some have been employed to assess weather impacts in Mexico in terms of human, environmental, and agricultural outcomes. In studying the impact of severe weather on health and cognitive development, Aguilar and Vicarelli (2011) use precipitation data at 0.5 degree resolution climate grids, which were generated by the Climate Research Unit and the Tyndall Centre for Climate Change Research, both at the University of East Anglia. Sáenz Romero et al. (2010) develop spatial climate models to estimate plant-climate relationships using thin plate smoothing splines of ANUSPLIN software, created by the Australian National University. Pollak and Corbett (1993) use spatial agroclimatic data to determine corn ecologies.

The underlying problem with these and other works that follow similar methodologies is their use of monthly climatic data. Using monthly climatic data is problematic due to the nonlinear effects of weather, which may be concealed when, for example, daily observations are averaged into monthly or seasonal variables. In effect, daily and even finer-scale weather data facilitate estimation of models that aim to identify nonlinearities and breakpoints in the effect of weather. Schlenker and Roberts (2009) use daily temperature data and find a nonlinear asymmetric relationship between weather and crops yields in the United States, with yields decreasing more rapidly above the optimal temperature vis-à-vis their increasing below the optimal temperature. The assumption of nonlinearity is particularly critical for studies like this one, where the researcher attempts to represent the relationship between weather and human physiology. In many studies, for the case of mortality, a *J*- or *U*-shaped curve has been found appropriate to describe the association, with elevated mortality being observed at temperature extremes and relatively lower mortality at moderate temperatures (Burgess et al. 2011; Curriero et al. 2002; Deschênes & Greenstone 2011; Huynen et al. 2001; Kunst, Looman & Mackenbach 1993.)

I use daily temperature and precipitation data from the North American Regional Reanalysis (NARR) model (NOAA 2012.) The NARR project is a long-term, high frequency, dynamically consistent meteorological and land surface hydrology dataset developed by the National Centers for Environmental Prediction (NCEP) as an extension of the NCEP Global Reanalysis, which is run over the North American Region. It covers the period 1979 to 2010 and data are available at three-hour intervals (i.e., eight data points per day), on a Northern Hemisphere Lambert Conformal Conic grid with a resolution of 0.3 degrees (32km)/45 layers at the lowest latitude. In addition to the modeling benefits of high spatial resolution, I employ NARR due to the model's good representation of extreme weather events, resulting from the model outputting all "native" (Eta) grid time-integrated quantities of water budget. In a recent study, Mesinger et al. (2006) compare the NARR precipitation for January 1998 (when the El Niño effect was underway) with observed precipitation. Their comparison shows that over land there is an extremely high agreement between NARR and observed precipitation, even over the complex western topography of Mexico.

Other variables could be employed for future work. The NARR dataset also includes information on wind speed, humidity, elevation, and other common climatic factors, but evidence shows that, at least for the most important crops of Mexico in terms of output (i.e., corn, sorghum, and wheat), temperature and precipitation are the two weather elements that can effectively inhibit plant growth and development to the point of crop failure (Ministry of Agriculture of Mexico 2012b.) Conversely, non-optimal values in altitude, soil quality, or light intensity requirements may only retard growth or reduce yields, but these factors are not likely to put crops at imminent risk (FAO 2007.)

I construct daily temperature data in two simple steps. First, I apply a spherical interpolation routine to the data: I take weighted averages of the daily mean temperature and accumulated precipitation of every NARR gridpoint within 30 kilometers of each municipality's geographic center, with the inverse squared haversine distance between the NARR gridpoint and the municipality centroid as the weighting factor.[18] Second, I distribute all the (365, or 366 for leap years) daily temperature estimates in a given year over 14 ranges: daily mean temperature lower than 10°C; daily mean temperature higher than 30°C, and 10 two-degree-wide ranges (i.e., 10°C-12°C, 12°C-14°C,..., 28°C-30°C) in between. Slicing the weather data into small intervals is important for the empirical strategy that will follow, for it maintains weather variation in any given specification, thus accounting for the nonlinear effects of weather extremes discussed above.

Figures 4 and 5 illustrate these ranges for the period 1979-2010. The height of the bars represents the weighted average number of days across municipality-by-year temperature and rainfall realizations, where the municipality-by-year's total population is the weight. The weighted average temperature is 18.6°C.

Table 3 summarizes the descriptive statistics for the temperature and precipitation variables employed.

5.4 Future Weather

In terms of future weather, I use data derived from the Hadley Center Coupled Model, version 3 (HadCM3), the most recent and complex coupled atmosphere-ocean general circulation model that has been developed by the Met Office Hadley Centre for Climate Change (2012), United Kingdom. The British Atmospheric Data Centre, which is part of the NERC National Centre for Atmospheric Science (NCAS), granted me access to its calculated trajectory data.

HadCM3 is one of the major models used in the IPCC Fourth Assessment Report (IPCC 2007), since it considers the interplay of several earth systems and is therefore considered the most accurate for climate predictions. It should be noted that, even

[18] The haversine distance measure is useful when the units are located on the surface of the earth and the coordinate variables represent the geographical coordinates of the spatial units and a spherical distance between the spatial units needs to be calculated. This is accomplished by calculating $d_{st} = r \times c$, where r is the mean radius of the Earth (6,371.009 kms); $c = 2\arcsin(\min(1, \sqrt{a}))$; $a = \sin^2\phi + \cos(\phi_1)\cos(\phi_2)\sin^2\lambda$; $\phi = \frac{1}{2}(\phi_2 - \phi_1) = \frac{1}{2}(x_2[t] - x_2[s])$; $\lambda = \frac{1}{2}(\lambda_2 - \lambda_1) = \frac{1}{2}(x_1[t] - x_1[s])$; $x_1[s]$ and $x_1[t]$ are the longitudes of point s and point t, respectively; and $x_2[s]$ and $x_2[t]$ are the latitudes of point s and point t, respectively.

though the state of climate modeling has advanced dramatically over the last several years, there is still much to learn, especially about the role of greenhouse gas emissions on climatic behavior (Karl & Trenberth 2003.) Thus, the HadCM3 predictions should be conceived of as two realizations from a superpopulation of models. The sources of uncertainty in these models and scenarios are unclear, so uncertainty cannot readily be incorporated into estimates of the impacts of climate change (Burgess et al 2011.)

Nevertheless, I selected HadCM3 due to primarily three reasons. First, as I discuss above, one of the critical issues in terms of studying the impact of weather is the frequency of the data, with daily data being preferred from an analytical standpoint, given that it allows the researcher to detect the abovementioned nonlinear effects of weather. I obtain daily temperature at 1.5m data from the HadCM3 model for the period December 1, 1989-November 30, 2100. Second, given that the model combines historical with projected data, I am able to account for model error in the analysis, reducing a potential source of bias when carrying out the empirical analysis. This will be explained in more detail when I discuss the methodological strategy in the following section. Third, its good simulation of current climate without using flux adjustments was a major advance at the time it was developed and it still ranks highly compared to other models in this respect (Reichler & Kim 2008.) It also has the capability to capture the time-dependent fingerprint of historical climate change in response to natural and anthropogenic forcings (Stott et al. 2000) which has made it a particularly useful tool in studies concerning the detection and attribution of past climate changes.

Predictions of climate change from the HadCM3 models are available for some of the greenhouse gas emissions scenarios described in the IPCC Fourth Assessment Report (2007.) In particular, my data are based on the predictions from the application of the A1FI scenario to the HadCM3 model. As discussed before, the A1 family of scenarios is characterized by rapid economic growth, a global population that reaches 9 billion in 2050 and then gradually declines, the quick spread of new and efficient technologies, and a convergent world, where income converges between regions and extensive social and cultural interactions worldwide occur. The A1FI scenario assumes, technologically speaking, a heavy reliance on fossil fuels. This is a "business-as-usual" scenario, which is the proper scenario to consider when judging policies to restrict greenhouse gas emissions (Deschênes & Greenstone 2011.) As these and other authors point out, given the abundant supply of inexpensive coal and other fossil fuels, a switch to alternative sources is unlikely without greenhouse gas taxes or the equivalent, so A1FI is a reasonable benchmark scenario. This scenario assumes the highest rate of greenhouse gas emissions, and thus needs to be seen as a worst-case outcome.

Typically, a global climate model breaks up the surface of the earth into a number of latitude/longitude grid boxes. It divides the atmosphere into layers, from the surface to the stratosphere, and does the same for the ocean, from the surface to the deepest waters. At each of the points on this three dimensional grid in the atmosphere a number of equations, derived from the basic laws of physics, are solved which describe the large-scale evolution of momentum, heat and moisture. Similar equations, but including different variables, are solved for the ocean. The atmospheric component of HadCM3, which I employ for my analysis, has 19 vertical levels in atmosphere with a horizontal resolution of 2.5 degrees of latitude by 3.75 degrees of longitude, which produces a global grid of 96 $\times$ 73 grid cells. This is equivalent to a surface resolution of about 417 km $\times$ 278 km at the Equator, reducing to 295 km $\times$ 278 km at 45 degrees of latitude (see Figure 6.)

I construct future daily temperature data in an analogous fashion to observed temperature data, with minor differences in the spherical interpolation routine: I take weighted averages of the daily mean temperature of every HadCM3 gridpoint within 300 kilometers from each municipality's geographic center, with the inverse squared haversine distance between the HadCM3 gridpoint and the municipality centroid as the weighting factor. Second, I distribute all the 360 (HadCM3 simulations often use a 360-day calendar, where each month is 30 days) daily temperature estimates in a given year over 14 ranges: daily mean temperature lower than 10°C; daily mean temperature higher than 30°C, and 10 two-degree-wide ranges (i.e., 10°C-12°C, 12°C-14°C,..., 28°C-30°C) in between. The projected change in the distribution of daily temperatures in Mexico is illustrated in Figure 7.

6 Econometric Strategy

In order to assess the welfare implication of climate change, it is necessary to first establish the relationship between current weather and mortality. An empirical specification that attempts to capture the full distribution of annual fluctuations in weather is based on the following equation:

$$Y_{mt} = \sum_{j=1}^{12} \theta_j temp_{mtj} + \alpha_m + \gamma_t + \lambda_r^1 t + \lambda_r^2 t^2 + \varepsilon_{mt} \tag{7}$$

where Y_{mt} is the (crude or an alternative) mortality rate in municipality m in year t (using logs virtually leaves the results unchanged, but for the sake of clarity, my analysis is carried out using levels.) $temp_{mtj}$ are the separate j temperature ranges described above for municipality m in year t = 1980, ..., 2010.[19]

The impact of temperature thus equals the sum of all j ranges. Notice that the only functional form restrictions in this specification are (1) the mortality impacts of temperature are constant within each 2-degree range, respectively, and (2) that all days with temperatures above (below or equal to) 30°C (10°C) have the same impact in terms of mortality.

[19] Additional regressions including precipitation ranges were run, but the results remained unchanged. The empirical specification without rainfall variables is also preferred from a methodological standpoint. There is insufficient and juxtaposing evidence in terms of the effects of climate-driven change on the evolution of precipitation patterns, particularly in regions affected by El Niño Southern Oscillation (ENSO), whose complex dynamics are limitedly understood and have not been well modeled as a result. As Seneviratne et al. (2012, p. 157) argue: "A caveat regarding all projections of future behavior of ENSO arises from systematic biases in the depiction of ENSO behavior through the 20th century by models (Randall et al., 2007; Guilyardi et al., 2009.) Leloup et al. (2008) for instance, demonstrate that coupled climate models show wide differences in the ability to reproduce the spatial characteristics of SST variations associated with ENSO during the 20th century, and all models have failings. They concluded that it is difficult to even classify models by the quality of their reproductions of the behavior of ENSO, because models scored unevenly in their reproduction of the different phases of the phenomenon. This makes it difficult to determine which models to use to project future changes in ENSO. Moreover, most of the models are not able to reproduce the typical circulation anomalies associated with ENSO in the Southern Hemisphere (Vera and Silvestri, 2009) and the Northern Hemisphere (Joseph & Nigam, 2006.) [...] Our current limited understanding means that it is not possible at this time to confidently predict whether ENSO activity will be enhanced or damped due to anthropogenic climate change, or even if the frequency of El Niño or La Niña episodes will change (Collins et al., 2010.)"

α_m is the fixed effect of municipality m. I include municipality fixed effects to control for the average differences across municipalities in any observable or unobservable predictors of log mortality rate, so that, for instance, demographic, socioeconomic, or clinical impacts will not be confounded with that of weather. Similarly, γ_t is the unrestricted time fixed effect of year t. These fixed effects control for time-varying differences in the dependent variable that are common across municipalities, such as the introduction of the Seguro Popular in 2003. Because such shocks are unlikely to have the same effect at the regional level (for instance, among Seguro Popular delegations, the pricing of prescription drugs varies greatly across regions), equation (7) also includes quadratic polynomial time trends λ_r for the r=5 mesoregions of Mexico (Northeast, Northwest, South, Center, and Center-West) which, at least in terms of weather, are fairly homogenous. Finally, ε_{mt} is the stochastic error term. Because observing a common variance structure over time is unlikely, my results are based on a cluster-correlated Huber-White covariance matrix estimator, which avoids the assumption of homoscedasticity (Wooldridge 2004.) In addition, my empirical specification is weighted by the squared root of the total municipal population, in an effort to correct for heteroskedasticity associated with municipal differences in estimation precision of mortality rates, having the additional advantage of presenting impacts on one person, rather than one municipality (Deschênes & Greenstone 2011.)

As discussed by Burgess et al. (2011) and Deschênes and Greenstone (2011), the validity of my empirical strategy for studying the weather-mortality relationship relies on the assumption that equation (7) yields unbiased estimates of the $\theta_j, \rho_k, \beta, \delta, \varphi$, and η vectors. Given the two-way fixed effect identification strategy employed, any omitted variables that are constant over time and/or particular to one municipality will not bias the estimates, even if the omitted variables are correlated with the explanatory variables. If weather variability is supposed to be random, then it is plausible to assume it is uncorrelated to unobserved mortality determinants.

I use the estimates based on the estimation of equation (7) for the various subsamples of interest to compute the predicted mortality impacts of climate change in Mexico in three future periods (2010-2039, 2040-2069, and 2070-2099) by carrying out the following routine:

1. Calculate the predicted change in temperature:

   ($\Delta T^{H}_{md,future\ period}$). Using the future climate data from the HadCM3 model (denoted by *H*), compute the difference in mean temperature between any given future period (i.e., 2070-2099) and this model's base period of 1990-2000. This is done for each municipality m and for each day of the year *d*. This subtraction is done to remove model error by using historical data.

2. Calculate the predicted end-of-century climate:

   ($T^{N}_{md,1980-2010} + \Delta T^{H}_{md,future\ period}$). This is simply the sum of the mean temperature for each day of the year and for each municipality over the 1980-2010 period (which is calculated using the NARR data, denoted by *N*) and the predicted change in temperature calculated above.

3. Generate j future temperature range variables:

   ($futuretemp_{mtj}$). For each municipality, distribute the future daily temperatures among the corresponding j-th temperature range. The resulting distribution is the HadCM3 predicted end-of-century temperature distribution.

4. Calculate future temperature distributional changes:

   ($\Delta Tbin_{mj} = futuretemp_{mj} - temp_{mj}$) This is the change in the number of days on which the mean temperature will fall into temperature range j by any given future period.

5. Calculate the predicted mortality-impact of climate change:

   ($\Delta\widehat{Y_{mt}}$). The predicted impact in municipality m is based on municipality-level predictions calculated as $\Delta\widehat{Y_{mt}} = \sum_{j=1}^{12} \widehat{\theta_j} \Delta T_{mj}$, where $\Delta\widehat{Y_{mt}}$ is the predicted change in the log mortality rate, $\widehat{\theta_j}$ is the estimated coefficient on temperature range j obtained by equation (7), and ΔT_{mj} is the change in the temperature distribution described above.

7 Results

In this section, I present the main findings of the analysis of the relationship between temperature and mortality in Mexico. In particular, I focus on the impact of extreme weather on death and how climate-change-induced warming is predicted to further exacerbate the negative effects of hot temperatures on human health.

Table 4b illustrates the relationship between severe temperatures and mortality (for reference, Table 4a also shows this relationship, using logs instead of levels for the dependent variable, death rate.) It presents the results based on equation (7) for the period 1990-2010, using data for 2,454 (99.9%) municipalities of Mexico. Although the impact of temperature was modeled using 11 2°C temperature ranges (defined as the number of days in a given temperature category in a municipality per year), for the purposes of clarity and specificity of analysis, I only present the estimates of the lowest three (coldest) and highest three (hottest) temperature ranges. Estimates in the center of the temperature distribution tended to be, in general, statistically insignificant at the conventional levels.

The first row of Panel A presents the results for crude (all-cause) mortality rates. It shows that extremely hot days (those with an average temperature higher than 26°C) are far more deadly than very cold days (defined as those with temperatures lower than 14°C.) While the three highest temperature ranges are large and significant, only the lowest temperature range is statistically different from zero and smaller in magnitude. Exposure to one day where the temperature is lower than 10°C is associated with roughly 0.2 additional deaths per 100,000 people. Conversely, the impact of an additional day with temperatures ranging between 28°C-30°C (relative to the mortality patterns on a day where temperature is in the 16°C-18°C range) equals 0.5 additional deaths per 100,000. Exposure to one day where the temperature is higher than 30°C leads to more than 0.8 additional deaths per 100,000.

As discussed previously in the literature review, there is substantial evidence that suggests that the impact of severe weather on humans is not uniform. Some groups of the population may be more vulnerable to extreme temperatures, given their human physiology characteristics. Rows 2-4 of Panel A in Table 4 support this argument. I investigate the impact of temperature on the mortality rates of three subpopulations of interest: infants (i.e., children less than one year old), young children (under the age of 5) and seniors (over 70 years of age.)

The results show that these groups are disproportionately affected by severe weather. The impact of cold days is inconclusive: while infant and child mortality rates seem to decrease with low temperatures, late-life mortality rate increases. However, hot weather does lead to highly significant and above the general population average increases in mortality. While in terms of the general population exposure to one day with temperatures higher than 26°C (relative to the impact of a day in the 16°C-18°C range) leads, on average, to 0.6 additional deaths per 100,000, it raises child mortality rate by 1.2 additional deaths per 100,000 people. Similarly, it increases infant mortality rate by more than 2.5 additional deaths per 100,000 live births. Moreover, nearly half of the crude mortality rate is explained by late-life mortality rate.

Alternative regional specifications shown in Panel B also reveal the same pattern. Extremely high temperatures are associated with higher mortality rates, while cold temperatures pose a more limited risk (both in terms of magnitude and significance) with regard to its impact on death. There are some interesting regional patterns that are worth noting. As predicted by theory and evidenced empirically, the magnitude of the impact of severe weather is considerably larger in rural areas than in urban centers. Exchanging a single day in the 16°C-18°C range for one in the highest temperature range leads to approximately 0.6 additional urban deaths per 100,000. Even though there are fewer days to identify the highest temperature range coefficient, the null hypothesis of equality is rejected at the 1% level. The impact at the rural level is almost tenfold: exchanging a single day in the 16°C-18°C range for one in the highest temperature range leads to approximately 5.3 additional rural deaths per 100,000. In this case, even though this impact is not significant at the conventional level, it should not be dismissed and assumed irrelevant. Given that large measurement variability (see Table 1) may mask important effects, the impact of extremely hot temperatures in rural regions should be at least deemed as "possibly harmful."

At the regional level, several interesting findings are observed. First, the impact of severe weather on mortality rates is spatially heterogeneous. The effect of the lowest temperature ranges from -0.2 to 0.3 additional deaths per 100,000. This effect is significant at the conventional level for two regions (Center-West and Center.) Similarly, the impact of the highest temperature ranges from 0.1 to 2.5 additional deaths per

100,000. This impact is significant at the 5% level for three regions (Northeast, Northwest and Center-West.) Second, in general, hotter/dryer regions fare worse than more temperate/more humid regions (see Figure 8) in terms of high-temperature impacts on mortality (low-temperature impacts are insignificant generally.) The estimated mortality impact of the above-30°C temperature range in the dryer/hotter regions (Northeast, Northwest, Center) is always statistically significant and ranges from 0.8-2.5 additional deaths per 100,000. Conversely, the estimated mortality impact of the above-30°C temperature range in the colder/more humid regions (Center-West and South) is never statistically significant and ranges from 0.1-0.3 additional deaths per 100,000. This is reflected in the test of equal regional estimates (bottom row of Table 4b) being rejected. These findings indicate that different levels of adaptation take place regionally. They also suggest that while hotter (colder) regions are better adapted to cope with severely hot (cold) weather in developed countries (Basu & Samet 2002), it may not be so in developing settings, where resource-constrained, agriculture-intensive economies are habitual.

Table 5 also reports the relationship between extreme weather and mortality rates, underscoring differences in age groups. Once again, with the exception of the coldest temperature ranges in the over-the-age-of-45 regressions, lower temperature ranges are in general non-significant. On the contrary, high-temperature ranges are usually associated with increases in the mortality rate across age groups. Notice that the effect of extremely high temperatures on death follows a *U*-shaped curve, showing that middle-aged people are the most resilient against extreme weather and that exposure to severe heat increases mortality in all but one age group (ages 20-24.) Older people are the most vulnerable group to the negative effects of extremely high temperatures: one extra day with mean temperature above 30°C leads to roughly 2 additional annual deaths per 100,000 people age 65-69; 4 additional annual deaths per 100,000 people age 70-74; and more than 5 additional annual deaths per 100,000 people age 75 and older.

Table 6 shows that, in the absence of any future effective mitigation (corresponding to the IPCC A1FI scenario), the impact of extreme weather on death is likely to be exacerbated as a result of climate change. The error-corrected Hadley 3 A1FI results indicate that climate change would have no statistically significant impact in the early

21^{st} century. However, halfway through the century, climate change would lead to a 4% increase in the annual mortality rate. By the end of the 21^{st} century, it would lead to a 9% increase in the annual mortality rate in Mexico. Regardless of the time period of analysis, the aggregate impact of weather on mortality is explained by statistically significant increases in the mortality rate as a result of the predicted increases in the frequency of hot days (8% increase in the annual mortality rate by the end of the century, significant at the 1% level) and statistically significant decreases in the mortality rate as a result of the predicted decreases in the frequency of cold days (2% decrease in the annual mortality rate by the end of the century, significant at the 1% level.) The overall effect is marginally statistically significant at the conventional significance levels for the mid-century and end-of-century time periods.

Table 7 reports alternative specifications of the mortality rate, focusing on three particularly vulnerable subpopulations: infants, children, and seniors. As expected, the effect of weather on death in these subpopulations is disproportionate given their higher susceptibility to severe weather. While climate change would lead to a 8.9% increase in the overall annual mortality rate, it would cause a 9.3% increase in the mortality rate among seniors. Similarly, it would increase infant and child mortality rates by 17.9% and 19.4% respectively. These estimates are precise and statistically significant at the conventional levels. In every alternative specification of the mortality rate, as climate gets warmer throughout the 21^{st} century, the effect of weather on death becomes more prominent. However, the effect size does not growth at a constant rate over time. For example, the overall impact of climate change on the infant mortality rate fluctuates from a 4% increase in the period 2010-2039 to a 10% increase in the period 2040-2069 to a 18% increase in the period 2070-2099. Similar patterns are observed for child and late-life mortality rates as well. In general, the increased mortality is mainly attributable to changes in the future temperature distribution, with significant increases in the number of hot days.

Table 8 breaks down the analysis by type of area. As expected, given the findings presented in Table 4, the results are sharply different for urban and rural areas. By the end of the century, annual mortality rates are predicted to increase by 40% in rural areas, and this estimate is statistically significant at the conventional levels. Again, the increased mortality is almost entirely attributable to the increase in the number of very hot days (where the mean temperature exceeds 30°C.) The urban mortality regression tells a completely different story. The predicted change in annual mortality is 5%, and is statistically distinguishable from zero at the 10% level only. Regardless of the time period, the predicted increases in annual mortality are larger and more concentrated in the rural areas. An important implication of these findings is that climate change will disproportionately affect the poor. In effect, in 2010 (the most recent year that data are available) while only 10% of urban households are considered "food-poor," i.e., unable to obtain a basic food basket even if all of the household's available income just is used for sustenance, 24% of rural households are confronted to alimentary poverty (Consejo Nacional de Evaluación de la Política de Desarrollo Social 2013.)

While significant changes in climate are predicted in this century, it is very likely that these changes will vary regionally. As a result, in terms of impact assessment processes, the regional scale is of more practical interest to decision-makers than the aggregate national scale. Table 9 reveals wide variation in the vulnerability of different regions to projected mean warming in every time period considered. It also indicates that the net welfare effect of climate change is likely to increase over time. For the period 2010-2039, the predicted overall effect of climate change is only statistically significant for two regions only. The Center-West region is expected to undergo a relatively small increase (3%) in the annual mortality rate. Conversely, the South region is expected to experience a decline of the same magnitude (3%) in the annual mortality rate. For the mid-century period, the predicted change in mortality is positive for all but one region (South) and is statistically different from zero in three of the five Mexican regions (Northwest, Northeast, and South.) Again, the South region is projected to experience a decline in annual mortality (9%), while predictions for the hottest regions of the country (Northwest and Northeast) estimate annual mortality increases of 9% and 5%, respectively. At the end of the century, regional differences will become more apparent. The largest increases in the annual mortality rate are projected to occur in the hottest regions of the country: the predicted effect of climate change on annual mortality, according to the error-corrected HadCM3 A1FI model, is a 11% increase in the Northeast and a 20% increase in the Northwest. On the contrary, the model predicts a significant decline in the annual death rate of the South region (11%.) The net effect of climate change on the annual mortality rate of the Center and Center-West region is positive, but smaller in magnitude (9% and 1%, respectively) and statistically equal to zero.

Finally, based on equation (7), Tables 11-13 present estimates of the impact of climate change on annual mortality rate, by age group, over the short, medium, and long terms, characterized by the error-corrected Hadley 3 A1FI predictions. Once again, I define short term as the average of the predictions for the years 2010-2039; medium term as the average of the predictions for the years 2040-2069; and long term as the average of the predictions for the years 2070-2099. The final row of Tables 11-13 aggregates all age-group-specific estimates to provide a weighted-by-age-group overall estimate. Columns (1)-(3) report the national age-group-specific estimate of the change in annual mortality for the extreme ranges of the temperature distribution (i.e., <10°C and >30°C) and an aggregate middle temperature category resulting from grouping the middle 9 temperature ranges (10°C-30°C.) Column (4) shows the total temperature impact, which is the sum of Columns (1)-(3). Column (5) reports the estimated percentage change in the annual mortality rate, which is calculated as the ratio of the change in the age group's annual mortality rate due to predicted climate change to its baseline annual mortality rate. Column (6) reports the change in life-years due to predicted climate change for each age category, based on a years-of-life-lost formulation that accounts for age-weighting and time-discounting, as previously discussed in the Data Construction section. For this calculation, I use data from the period life table for Mexico I construct for this analysis, and which I replicate in Table 10. A negative value in Column (6) corresponds to *gains* of life years, i.e., climate change is likely to lead to a decline in death counts.

Over the short term, I find that the impact of climate change is inconsequential. The total impact on annual crude mortality rate is statistically not different from zero. Although non-significant at conventional levels, the results show that, if anything, climate change would lead overall to 750 fewer deaths per 100,000, a 0.3% decline in the annual mortality rate. Notice that this non-significant result is the outcome of two opposite forces balancing each other out: a statistically significant increase in the mortality rate due to a higher frequency of very-high-temperature days and a statistically significant decline in the mortality rate due to a lower frequency of very-low-temperature days. In terms of age groups, only infants and children under five are negatively affected by climate change. It is the sole age group for which the impact on annual mortality rate is statistically significant (in the short term.) I find a 1.9% increase in this age group's mortality rate, equivalent to 538 additional deaths per 100,000 per year, or an annual loss of 34,850 years of life lost.

Over the medium term, the impact of climate change is significantly more pronounced than in the short term. The total impact on annual crude mortality rate is statistically different from zero at the 5% level. The results show that climate change would lead overall to 3,878 additional deaths per 100,000, a 3.9% increase in the annual mortality rate. Once again, this effect is explained by a future temperature distribution with more recurrent hot days and less frequent cold days. As discussed in the literature review, two groups are most vulnerable to climate change: infants and young children, and seniors. My analysis points to a 5.8% increase in annual mortality rate among seniors between the ages of 70 and 74 (the results for the 75+ age group are statistically zero), while the annual mortality rate for infants and young children is expected to increase by 9.5%. This is equivalent to 797 and 2,585 additional annual deaths per 100,000, respectively. Combined, this equals to roughly 782,000 years of life lost annually.

By the end of the century, the impact of climate change will be further exacerbated. Over the long term, the total impact on annual crude mortality rate is statistically different from zero at the 1% level. The results show that climate change would lead overall to 10,001 additional deaths per 100,000, a 8.9% increase in the annual mortality rate. In other words, the impact of climate change on mortality between the mid and the end-of-century is expected to more than double. The impact of climate change on vulnerable groups will be intensified as well. My analysis points to a 11.0% increase in annual mortality rate among seniors between the ages of 70 and 74, while the annual mortality rate for infants and young children is expected to increase by 19.3%. This is equivalent to 1,689 and 5,221 additional annual deaths per 100,000, respectively. Overall, the results suggest that climate change would lead to a loss of more than 3.1 million life-years per annum.

8 Conclusion

Climate change is a clear challenge for the planet, not only for the damage it is expected to inflict on underdeveloped economic systems, but also for the social inequities it is likely to exacerbate. This is especially true for countries like Mexico, where the number of people relying on primary economic activities is significantly higher than in industrialized nations, and where roughly half of the population lives under abject poverty or does not have access to well-functioning credit and insurance markets. Without such markets, it will be difficult for many people to mitigate the negative effects of global warming and future severe weather, both on their income sources and their own health.

In this paper, I connect future climate change to adverse health outcomes. I show that the warmer the climate becomes, the higher the all-cause mortality rate. In the absence of any future effective mitigation or adaptation, my results indicate that climate change would have no statistically significant impact in the early 21st century. However, halfway through the century, climate change would lead to a 4% increase in the annual mortality rate. By the end of the 21st century, it would lead to a 9% increase in the annual mortality rate in Mexico.

I find that climate change will have its greatest effect in deprived areas and vulnerable segments of the population. Infants, children and seniors will be disproportionately affected given their higher susceptibility to severe weather. While climate change would lead to a 8.9% increase in the overall annual mortality rate, my analysis points to a 11.0% increase in annual mortality rate among seniors between the ages of 70 and 74, while the annual mortality rate for infants and young children is expected to increase by 19.3%. This is equivalent to 1,689 and 5,221 additional annual deaths per 100,000, respectively. In all, the results suggest that climate change would lead to a loss of more than 3.1 million life-years per annum (equivalent to one life-year lost every ten seconds.) Equally, those who have the fewest assets (and who have contributed least to climate change) will be hit the hardest: while annual mortality rates are projected to increase by 5% in cities by the end of the century, the expected change in rural areas, where the majority of the poor is concentrated, is 40%.

In addition, I present evidence that there is wide variation in the vulnerability of different Mexican regions to projected climate change. While I find large increases in the annual mortality rate in both the Northeast and the Northwest (the hottest regions of the country), my model predicts a significant decline in the annual death rate of the South region.

In the light of these findings, there are several key issues that need to be considered as the projected impact of climate change materializes. It is important to emphasize that the most critical social policy issue regarding climate change should be the reduction of health risks among the most vulnerable. Four recommendations towards this end are presented below:

1. In terms of knowledge generation, it is important to produce more and better data on both hydrometeorological phenomena and health outcomes. While mortality data, as I evidence in this paper, are of high quality and disaggregation, other relevant health outcomes, such as morbidity and the incidence of particular diseases, are currently unavailable. To operationalize truly useful vulnerability assessments and risk monitoring, disease transmission patterns, municipality-specific epidemiological and meteorological station data, and other complex information is required.
2. In terms of future research implications, one proposal is to focus on the differentiated impact of climate on alternative human health measures. Similarly, the policy, economic, and environmental implications of the regional variability of climate impact is worth investigated and need to be addressed. The methodology I introduce in this paper can be employed to develop estimates of the welfare cost of climate change (not only in terms of health, but also agricultural incomes, nutrition, or energy consumption) in other countries at risk. Finally, in addition to understanding patterns of risk, it is important to evaluate the spatial vulnerability of indigenous groups, households with young children or seniors, families living in irregular settlements, and other populations susceptible

to severe weather in order to reduce their risk. A geographic information system analysis for rural and urban-poor communities is thus indispensable to identify their vulnerability and implement *ad hoc* policies to their capacity and capabilities.

3. In terms of poverty alleviation, it is critical to target climate-change-adaptation efforts to the specific needs of vulnerable populations, primarily the poor, infants, and the elderly. Basic health infrastructure in rural Mexico is scarce and deficient. Notorious health inequities exist in Mexico, associated with high prevalence of social exclusion, particularly in the rural regions of the country (González Pérez et al. 2008.) A more substantive health reform aimed at redistribution through fiscal policy and access of the vulnerable to the health system is essential. The development of the clinical and human capacity of the health system that resonates with local preferences is necessary to give way to coherent, bottom-up community-based health planning that provides the foundation for an effective public health response to the many climate-induced threats to health (Carmin & Zhang 2009; Costello et al. 2009.) Likewise, as I will show in the next paper, state interventions in the form of safety net development, conditional-cash-transfer programs, nutritional programs, especially for households with infants and young children, effective disaster coping preparedness, or other mechanisms to enhance the adaptive capacity of disadvantaged households and communities to deal with climatic variability and risks leads to sustained improvements in welfare.
4. In terms of institutional coordination, a more solid framework to have all the levels of government reinforce, rather than exclude, one another to provide an effective climate-change-coping response, particularly in poor communities, is required. Rather than having the states and municipalities implement fragmented and likely contradictory strategies to cope with climate change,[20] a connection with active broad federal responses, like the National Climate Change Strategy, would be more conducive to multisectoral policy implementation ca-

[20] See for instance the Climate Change Program of Action of the State of Nuevo León or Mexico City's Climate Action Local Strategy.

pacities, responsive to market failures and effective to facilitate access to more resources for communities in need. In terms of research, it would be useful to understand what is driving municipalities and states to initiate local climate adaptation planning and the extent of its variation.

9 References

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Table 1. Mortality Rates in Mexico, 1990-2011, by Type of Area

	Pooled (1)	Rural (2)	Urban (3)
Crude mortality rate	4.8	9.1	4.9
	(1.4)	(34.5)	(1.9)
Child mortality rate	3.1	8.8	3.5
	(3.8)	(64.1)	(11.2)
Late-life mortality rate	2.0	3.5	2.1
	(0.9)	(14.5)	(1.0)

Note: Municipalities may consist of urban areas only, rural areas only, or a combination of both. All statistics are weighted by total municipal population. Standard deviations in parentheses.

Table 2. Crude (All-Cause) Mortality Rate in Mexico, 1990-2011, by Age Group

Age group	Crude mortality rate (1)	Age group	Crude mortality rate (1)	Age group	Crude mortality rate (1)
Pooled	4.8	25–29	1.8		
	(1.4)		(1.2)		
0–4	4.6	30–34	1.8	55–59	9.8
	(2.9)		(1.1)		(3.7)
5–9	0.3	35–39	2.2	60–64	13.9
	(0.4)		(1.3)		(4.9)
10–14	0.4	40–44	3.0	65–69	21.4
	(0.3)		(1.7)		(7.3)
15–19	0.8	45–49	4.4	70–74	31.2
	(0.6)		(2.1)		(10.7)
20–24	1.2	50–54	6.3	75 and over	79.5
	(0.8)		(2.6)		(18.9)

Note: All-cause mortality by age group is the annual number of deaths in a given age group per the population in that age group (expressed per 1,000.) All statistics are weighted by total municipal population within each age group. Standard deviations in parentheses.

Table 3. Relevant Climate Outcomes in Mexico, 1979-2009, by Type of Area

Rates	Pooled (1)	Rural (2)	Urban (3)
Daily mean temperature (°C)	18.5	17.4	18.5
	(4.4)	(3.9)	(4.4)
Annual average rainfall (mm)	712.8	678.9	713.0
	(419.1)	(332.7)	(419.5)
Annual degree-days (over 30°C)	11.6	6.8	11.6
	(45.5)	(30.0)	(45.5)
Annual degree-days (below 10°C)	30.1	38.7	30.1
	(54.7)	(57.8)	(54.7)
Annual millimeters-days (over 8mm)	174.8	129.3	175.1
	(225.1)	(139.8)	(225.4)
Annual millimeters-days (below 3mm)	779.7	764.9	779.8
	(122.7)	(120.6)	(122.8)

Note: If fewer than 2,500 residents live in a given municipality, such a municipality is considered "rural." All statistics are weighted by total municipal population. Standard deviations in parentheses.

Table 4. Estimates of the Impact of Extreme Temperatures on Several Annual Log and Actual Mortality Rates, by Regions and Type of Area

a. Impact on annual log mortality rates

	Days < 10 ℃		Days 10 ℃-12 ℃		Days 12 ℃-14 ℃		Days 26 ℃-28 ℃		Days 28 ℃-30 ℃		Days > 30 ℃	
	(1)		(2)		(3)		(4)		(5)		(6)	
Panel A. Pooled estimates												
Crude	0.00032	***	-0.00093		0.00035		0.00116	***	0.00081	***	0.00153	***
(n=48,583)	(0.00009)		(0.00091)		(0.00031)		(0.00018)		(0.00022)		(0.00027)	
Child	-0.00073	***	-0.00246	**	-0.00075		0.00115	**	0.00154	**	0.00128	*
(n=30,755)	(0.00021)		(0.00111)		(0.00047)		(0.00055)		(0.00062)		(0.00069)	
Late-life	0.00043	***	-0.00131		0.00058	*	0.00140	***	0.00076	***	0.00166	***
(n=48,219)	(0.00010)		(0.00092)		(0.00033)		(0.00023)		(0.00026)		(0.00035)	
Panel B. Alternative specifications												
Urban	0.00029	***	-0.00127		0.00011		0.00052	**	0.00037		0.00095	***
(n–29,206)	(0.00010)		(0.00094)		(0.00033)		(0.00021)		(0.00025)		(0.00030)	
Rural	-0.00077		0.00214		-0.00018		0.00311	**	0.00284	**	0.00393	***
(n=46,384)	(0.00055)		(0.00144)		(0.00072)		(0.00136)		(0.00139)		(0.00102)	

Table 4., continued

	a. Impact on log annual mortality rates											
	Days < 10 ℃		Days 10 ℃-12 ℃		Days 12 ℃-14 ℃		Days 26 ℃-28 ℃		Days 28 ℃-30 ℃		Days > 30 ℃	
	(1)		(2)		(3)		(4)		(5)		(6)	
Panel B. Alternative specifications												
Northwest	0.00000		-0.00094		-0.00015		0.00039		0.00078	**	0.00235	***
(n=1,966)	(0.00031)		(0.00084)		(0.00050)		(0.00041)		(0.00035)		(0.00053)	
Northeast	0.00008		0.00044		0.00064		0.00103	**	0.00067		0.00162	**
(n=4,760)	(0.00018)		(0.00071)		(0.00060)		(0.00042)		(0.00058)		(0.00073)	
Center-West	-0.00036	*	-0.00010		0.00048	**	0.00097	***	0.00161	***	0.00055	
(n=9,118)	(0.00019)		(0.00034)		(0.00024)		(0.00038)		(0.00039)		(0.00104)	
Center	0.00044		-0.00123		0.00008		0.00317	***	0.00582	***	-0.00230	
(n=10,559)	(0.00032)		(0.00155)		(0.00050)		(0.00104)		(0.00182)		(0.00162)	
South	0.00014		0.00184	***	0.00109	***	0.00048	*	-0.00002		0.00029	
(n=22,180)	(0.00015)		(0.00064)		(0.00035)		(0.00028)		(0.00029)		(0.00033)	
p-value (Wald tests of regional equality)	0.006		0.090		0.564		0.069		0.000		0.002	

Note: Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by total municipal population. Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Temperature exposure is modeled with 11 temperature-day ranges defined as the number of days in a given temperature category in a municipality-year. Only the estimates on the lowest three (coldest) and highest three (hottest) temperature ranges are reported for compactness.

Table 4., continued

	b. Impact on annual mortality rates											
	Days < 10℃		Days 10°-12℃		Days 12°-14℃		Days 26°-28℃		Days 28°-30℃		Days > 30℃	
	(1)		(2)		(3)		(4)		(5)		(6)	
Panel A. Pooled estimates												
Crude	0.174	***	0.025		0.004		0.614	***	0.530	***	0.812	***
(n=48,664)	(0.051)		(0.243)		(0.117)		(0.099)		(0.111)		(0.131)	
Infant	-0.598	*	-3.971	**	-0.118		3.204	***	1.574	*	2.774	***
(n=48,656)	(0.346)		(1.802)		(0.697)		(0.687)		(0.930)		(0.938)	
Child	-0.274	***	-0.766	**	-0.174		1.029	***	1.657	***	0.897	***
(n=48,656)	(0.092)		(0.344)		(0.216)		(0.258)		(0.322)		(0.286)	
Late-life	0.097	***	-0.025		0.019		0.261	***	0.186	***	0.356	***
(n=48,664)	(0.023)		(0.094)		(0.048)		(0.045)		(0.051)		(0.067)	
Panel B. Alternative specifications												
Urban	0.207	***	0.013		-0.121		0.349	***	0.301	**	0.573	***
(n=30,777)	(0.057)		(0.262)		(0.131)		(0.122)		(0.135)		(0.156)	
Rural	-1.022		5.637		-0.398		2.021		3.864		5.256	
(n=48,023)	(2.151)		(4.077)		(8.946)		(3.994)		(5.190)		(5.016)	

Table 4., continued

	b. Impact on annual mortality rates											
	Days < 10 ℃		Days 10 °-12 ℃		Days 12 °-14 ℃		Days 26 °-28 ℃		Days 28 °-30 ℃		Days > 30 ℃	
	(1)		(2)		(3)		(4)		(5)		(6)	
Panel B. Alternative specifications												
Northwest	-0.016		-0.486		-0.104		0.173		0.386	**	1.056	***
(n=1,975)	(0.135)		(0.384)		(0.233)		(0.200)		(0.168)		(0.248)	
Northeast	0.053		0.412		0.327		0.490	**	0.367		0.792	**
(n=4,760)	(0.087)		(0.315)		(0.265)		(0.202)		(0.260)		(0.352)	
Center-West	-0.199	**	-0.049		0.145		0.482	***	0.734	***	0.296	
(n=9,119)	(0.088)		(0.155)		(0.113)		(0.169)		(0.177)		(0.382)	
Center	0.327	**	0.108		0.092		1.728	***	2.801	***	2.531	***
(n=10,562)	(0.149)		(0.455)		(0.252)		(0.427)		(0.510)		(0.433)	
South	0.021		1.033	***	0.545	***	0.231	*	0.095		0.079	
(n=22,248)	(0.072)		(0.297)		(0.166)		(0.123)		(0.129)		(0.140)	
p-value (Wald tests of regional equality)	0.002		0.020		0.259		0.020		0.000		0.034	

Note: Crude and late-life mortality rates are defined as the annual number of deaths per 100,000 people. Infant and child mortality rates are defined as the annual number of deaths per 100,000 live births. Age-specific mortality rates are defined as the annual number of deaths per 100,000 people in the specified group. Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by total municipal population. Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Temperature exposure is modeled with 11 temperature-day ranges defined as the number of days in a given temperature category in a municipality-year. Only the estimates on the lowest three (coldest) and highest three (hottest) temperature ranges are reported for compactness.

Table 5. Estimates of the Impact of Extreme Temperatures on All-Cause Annual Mortality Rate, by Age Group

	Impact on annual mortality rates											
	Days < 10 ℃		Days 10 ℃-12 ℃		Days 12 ℃-14 ℃		Days 26 ℃-28 ℃		Days 28 ℃-30 ℃		Days > 30 ℃	
	(1)		(2)		(3)		(4)		(5)		(6)	
Panel A. Pooled estimates												
All ages (unadjusted)	0.174	***	0.025		0.004		0.614	***	0.530	***	0.812	***
(*n*=48,664)	(0.051)		(0.243)		(0.117)		(0.099)		(0.111)		(0.131)	
All ages (adjusted)	0.154	**	0.030		0.039		0.447	***	0.441	***	0.547	***
(*n*=48,664)	(0.071)		(0.296)		(0.147)		(0.147)		(0.166)		(0.182)	
Panel B. Age-group specifications												
Age 0–4	0.157	*	0.207		-0.046		1.595	***	1.447	***	1.702	***
(*n*=48,623)	(0.081)		(0.366)		(0.201)		(0.171)		(0.262)		(0.218)	
Age 5–9	0.002		-0.021		-0.001		0.030		0.064	**	0.044	
(*n*=48,624)	(0.006)		(0.024)		(0.019)		(0.023)		(0.026)		(0.029)	
Age 10–14	0.009		0.029		0.005		0.058	***	0.060	**	0.069	**
(*n*=48,624)	(0.006)		(0.024)		(0.016)		(0.021)		(0.025)		(0.029)	
Age 15–19	0.021		0.016		-0.036		0.017		0.046		0.076	
(*n*=48,624)	(0.013)		(0.054)		(0.029)		(0.041)		(0.043)		(0.053)	
Age 20–24	0.042	**	-0.078		-0.027		-0.107		-0.030		-0.016	
(*n*=48,624)	(0.020)		(0.081)		(0.042)		(0.061)		(0.060)		(0.077)	
Age 25–29	0.031		0.061		0.030		0.140		0.139		0.326	***
(*n*=48,624)	(0.036)		(0.146)		(0.085)		(0.098)		(0.100)		(0.118)	
Age 30–34	0.030		-0.056		0.015		0.100		0.232	***	0.148	
(*n*=48,624)	(0.031)		(0.112)		(0.072)		(0.088)		(0.083)		(0.109)	
Age 35–39	0.056		0.117		-0.055		0.160		0.225	**	0.247	***
(*n*=48,624)	(0.038)		(0.142)		(0.092)		(0.109)		(0.104)		(0.111)	

Table 5., continued

	Impact on annual mortality rates					
	Days < 10 ℃	Days 10 ℃-12 ℃	Days 12 ℃-14 ℃	Days 26 ℃-28 ℃	Days 28 ℃-30 ℃	Days > 30 ℃
	(1)	(2)	(3)	(4)	(5)	(6)
Age 40–44	0.091	0.013	-0.039	0.212 *	0.255 **	0.312 **
(n=48,624)	(0.049)	(0.203)	(0.116)	(0.116)	(0.119)	(0.142)
Age 45–49	0.123 *	0.063	-0.120	0.173	0.219	0.161
(n=48,624)	(0.068)	(0.274)	(0.155)	(0.149)	(0.162)	(0.189)
Age 50–54	0.196 **	0.282	0.084	0.519 **	0.539 **	0.285
(n=48,624)	(0.087)	(0.360)	(0.181)	(0.212)	(0.216)	(0.269)
Age 55–59	0.238 **	0.201	-0.339	0.378	0.487	0.734 **
(n=48,624)	(0.121)	(0.579)	(0.249)	(0.261)	(0.304)	(0.354)
Age 60–64	0.314 *	0.569	0.269	0.692 *	0.941 **	1.263 ***
(n=48,624)	(0.190)	(0.894)	(0.396)	(0.405)	(0.417)	(0.466)
Age 65–69	0.719 **	0.342	0.779	1.528 ***	1.606 **	1.952 ***
(n=48,624)	(0.298)	(1.224)	(0.611)	(0.588)	(0.656)	(0.712)
Age 70–74	0.628	-0.621	0.364	3.428 ***	3.201 ***	4.301 ***
(n=48,624)	(0.440)	(1.873)	(0.832)	(0.804)	(0.876)	(1.027)
Age 75+	3.306 ***	-1.337	1.902	4.985 ***	3.423 **	5.298 ***
(n=48,624)	(1.027)	(4.163)	(1.770)	(1.571)	(1.740)	(1.912)

Note: All-cause mortality by age group is the annual number of deaths in a given age group per the population in that age group (expressed per 100,000.) Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by total municipal population within each age group. Age-group specific estimates were combined into an age-adjusted pooled estimate by taking a weighted average of the age-specific estimates, where the weight is the average population in each age group. Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Temperature exposure is modeled with 11 temperature-day ranges defined as the number of days in a given temperature category in a municipality-year. Only the estimates on the lowest three (coldest) and highest three (hottest) temperature ranges are reported for compactness.

Table 6. Estimates of the Impact of Climate Change on All-Cause log Annual Mortality Rate, by Time Period and Segment of the Future Temperature Distribution

	Impact on log annual crude mortality rate							
	Days < 10°C		Days 10°-30°C		Days >30°C		Total impact	
	(1)		(2)		(3)		(4)	
All-cause mortality								
2010-2039	-0.01870	***	0.01172	**	0.00369	***	-0.00329	
(n=49,080)	(0.00520)		(0.00541)		(0.00068)		(0.00757)	
2040-2069	-0.02057	***	0.02421		0.03552	***	0.03916	**
(n=49,080)	(0.00572)		(0.01475)		(0.00650)		(0.01705)	
2070-2099	-0.02090	***	0.02954		0.08038	***	0.08903	***
(n=49,080)	(0.00581)		(0.01811)		(0.01472)		(0.02419)	

Note: Estimates based on error-corrected Hadley CM3 A1FI model. Temperature exposure is modeled with 11 temperature-day ranges defined as the number of days in a given temperature category in a municipality-year. Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by total municipal population, with a sample size of 49,080. Huber-White standard errors in parentheses, taking climate-change predictions as constants. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7. Estimates of the Impact of Climate Change on Alternative log Annual Mortality Rates, by Time Period and Segment of the Future Temperature Distribution

	Impact on log annual mortality rates							
	Days < 10°C		Days 10°-30°C		Days >30°C		Total impact	
	(1)		(2)		(3)		(4)	
Infant mortality								
2010-2039	0.01780	**	0.01524		0.00367	**	0.03671	**
	(0.00810)		(0.00997)		(0.00165)		(0.01632)	
2040-2069	0.01957	**	0.04755		0.03537	**	0.1025	**
	(0.00890)		(0.02900)		(0.01594)		(0.04483)	
2070-2099	0.01988	**	0.07938	*	0.08005	**	0.17931	**
	(0.00905)		(0.04305)		(0.03607)		(0.07485)	
Child mortality								
2010-2039	-0.00192		0.01606	*	0.00553	***	0.01968	
	(0.00782)		(0.00895)		(0.00138)		(0.01425)	
2040-2069	-0.00211		0.04468	*	0.05328	***	0.09585	**
	(0.00861)		(0.02566)		(0.01325)		(0.03861)	
2070-2099	-0.00214		0.07518	**	0.12056	***	0.19360	***
	(0.00874)		(0.03716)		(0.02999)		(0.06372)	

Table 7., continued

	Impact on log annual mortality rates							
	Days < 10°C		Days 10°-30°C		Days >30°C		Total impact	
	(1)		(2)		(3)		(4)	
Late-life mortality								
2010-2039	-0.02523	***	0.01429	**	0.00399	***	-0.00695	
	(0.00577)		(0.00564)		(0.00087)		(0.00817)	
2040-2069	-0.02775	***	0.03040	**	0.03843	***	0.04109	**
	(0.00634)		(0.01543)		(0.00835)		(0.01944)	
2070-2099	-0.02819	***	0.03391	*	0.08697	***	0.09269	***
	(0.00644)		(0.01957)		(0.01889)		(0.02960)	

Note: Estimates based on error-corrected Hadley CM3 A1FI model. Temperature exposure is modeled with 11 temperature-day ranges defined as the number of days in a given temperature category in a municipality-year. Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by total municipal population, with a sample size of 49,080. Huber-White standard errors in parentheses, taking climate-change predictions as constants. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8. Estimates of the Impact of Climate Change on log Annual Mortality Rate, by Type of Area, Time Period and Segment of the Future Temperature Distribution

	Impact on log annual mortality rates							
	Days < 10°C		Days 10°-30°C	Days >30°C		Total impact	
	(1)		(2)	(3)		(4)	
Urban mortality							
2010-2039	-0.01702	***	0.00951	0.00228	***	-0.00523	
	(0.00582)		(0.00592)	(0.00075)		(0.00841)	
2040-2069	-0.01872	***	0.01829	0.02191	***	0.02148	
	(0.00641)		(0.01610)	(0.00723)		(0.01888)	
2070-2099	-0.01902	***	0.01688	0.04958	***	0.04744	*
	(0.00651)		(0.02009)	(0.01635)		(0.02703)	
Rural mortality							
2010-2039	0.04456		0.02169	0.00945	*	0.07571	
	(0.03292)		(0.02396)	(0.00500)		(0.04787)	
2040-2069	0.04901		0.06887	0.09103	*	0.20891	*
	(0.03621)		(0.06710)	(0.04811)		(0.12387)	
2070-2099	0.04979		0.14154	0.20600	*	0.39733	**
	(0.03679)		(0.09356)	(0.10888)		(0.20255)	

Note: Estimates based on error-corrected Hadley CM3 A1FI model. Temperature exposure is modeled with 11 temperature-day ranges defined as the number of days in a given temperature category in a municipality-year. Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by total municipal population, with a sample size of 49,080. Huber-White standard errors in parentheses, taking climate-change predictions as constants. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9. Estimates of the Impact of Climate Change on log Annual Mortality Rate, by Region, Time Period and Segment of the Future Temperature Distribution

	Impact on log annual mortality rates			
	Days < 10°C	Days 10°-30°C	Days >30°C	Total impact
	(1)	(2)	(3)	(4)
Northwest				
2010-2039	-0.00027	0.01375	0.00565 ***	0.01914
	(0.01900)	(0.01022)	(0.00132)	(0.02679)
2040-2069	-0.00029	0.04117	0.05443 ***	0.09531 *
	(0.02090)	(0.03303)	(0.01269)	(0.05630)
2070-2099	-0.00030	0.08206 *	0.12317 ***	0.20494 **
	(0.02123)	(0.04922)	(0.02872)	(0.08341)
Northeast				
2010-2039	-0.00481	0.00477	-0.00390 **	0.00385
	(0.01103)	(0.00979)	(0.00180)	(0.02060)
2040-2069	-0.00529	0.01728	0.03753 **	0.04952 ***
	(0.01213)	(0.03123)	(0.01736)	(0.01333)
2070-2099	-0.00538	0.02945	0.08493 **	0.10901 ***
	(0.01232)	(0.05361)	(0.03929)	(0.03119)
Center-West				
2010-2039	0.02121 *	0.00761	0.00132	0.03014 **
	(0.01142)	(0.00576)	(0.00257)	(0.01495)
2040-2069	0.02333 *	0.01284	0.01271	0.04887
	(0.01256)	(0.01762)	(0.02471)	(0.03721)
2070-2099	0.02370 *	0.03388	0.02876	0.08634
	(0.01276)	(0.02794)	(0.05593)	(0.06997)

Table 9., continued

	Impact on log annual mortality rates							
	Days < 10°C		Days 10°-30°C		Days >30°C		Total impact	
	(1)		(2)		(3)		(4)	
Center								
2010-2039	-0.02552		0.05655	***	-0.00552		0.02550	
	(0.01941)		(0.01667)		(0.00400)		(0.03034)	
2040-2069	-0.02807		0.12500	***	-0.05317		0.04376	
	(0.02135)		(0.04307)		(0.03848)		(0.05652)	
2070-2099	-0.02852		0.15950	***	-0.12032		0.01066	
	(0.02169)		(0.06314)		(0.08709)		(0.09325)	
South								
2010-2039	-0.00845		-0.02583	***	0.00070		-0.03358	***
	(0.00886)		(0.00626)		(0.00082)		(0.00899)	
2040-2069	-0.00929		-0.08645	***	0.00672		-0.08903	***
	(0.00974)		(0.01868)		(0.00798)		(0.02217)	
2070-2099	-0.00943		-0.11319	***	0.01520		-0.10742	***
	(0.00990)		(0.02555)		(0.01806)		(0.03575)	

Note: Estimates based on error-corrected Hadley CM3 A1FI model. Temperature exposure is modeled with 11 temperature-day ranges defined as the number of days in a given temperature category in a municipality-year. Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by total municipal population, with a sample size of 49,080. Huber-White standard errors in parentheses, taking climate-change predictions as constants. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 10. Period Life Table for Mexico

Age interval (1)	Average population (2)	Average age at death (3)	Life expectancy at age range (4)	ARS probability of dying (5)	Survivors to age range (6)	Age-range-specific survivor ratio (7)
Age 0–4	10,453,800	0.5	75.6	0.00236	99,081	0.99357
Age 5–9	10,840,879	6.9	69.4	0.00118	98,463	0.99870
Age 10–14	10,737,539	12.2	64.2	0.00137	97,868	0.99593
Age 15–19	10,186,748	17.3	59.3	0.00220	97,495	0.99602
Age 20–24	9,030,924	22.1	54.6	0.00280	99,450	0.99923
Age 25–29	7,813,376	27.0	49.9	0.00323	95,311	0.98917
Age 30–34	7,098,699	32.0	45.0	0.00406	95,665	0.98768
Age 35–39	6,431,469	37.0	40.2	0.00570	95,222	0.98358
Age 40–44	5,230,683	42.0	35.4	0.00895	94,313	0.97866
Age 45–49	4,320,078	47.0	30.8	0.01473	92,669	0.96994
Age 50–54	3,560,547	52.1	26.2	0.02414	90,286	0.95807
Age 55–59	2,739,610	57.0	22.0	0.03966	86,389	0.93790
Age 60–64	2,298,072	62.1	17.9	0.06628	79,853	0.90170
Age 65–69	1,709,116	67.0	14.2	0.11286	69,493	0.83916
Age 70–74	1,304,626	72.0	10.9	0.18996	54,169	0.73570
Age 75+	1,948,281	84.5	4.3	0.53830	4,513	0.31428

Note: Average population and average age at death data are for the 1990-2010 period. Columns (4)-(7) estimates based on the Coale-Demeny West model life table system, assuming a life expectancy of 75 years for both genders. Life expectancy patterns for males and females are combined into age-range-specific pooled patterns by taking a weighted average of the age-range-specific patterns, where the weights are the average population of males and females over the 1990-2010 period. Age-range-specific probability of dying is the probability of death occurring within one year for each age group. Survivors-to-age range is the number of survivors out of 100,000 born alive. The age-range-specific survivor ratio is the probability of living through a given age range. ARS: Age-range-specific.

Table 11. Estimates of the Impact of Short-Term Climate Change on Annual (All-Cause) Mortality Rate, by Age Group and Segment of the Future Temperature Distribution

	Impact on annual crude (all-cause) mortality rate					
	Days <10°C	Days 10°-30°C	Days >30°C	Total impact	% Change in rate	Years-life lost
	(1)	(2)	(3)	(4)	(5)	(6)
2010-2039						
Age 0–4	-388 *	713 ***	213 ***	538 **	1.9	34,850
	(202)	(169)	(27)	(250)	(1.4)	
Age 5–9	-6	41 ***	6	41	2.3	3,680
	(16)	(14)	(4)	(25)	(1.8)	
Age 10–14	-22	18	9 **	5	0.7	139
	(16)	(14)	(4)	(23)	(1.6)	
Age 15–19	-51	24	9	-18	0.0	-
	(32)	(26)	(6)	(45)	(1.8)	
Age 20–24	-92 **	11	-2	-83	-0.4	-1,013
	(45)	(32)	(8)	(57)	(1.5)	
Age 25–29	-60	26	31 ***	-3	-0.4	-29
	(70)	(47)	(11)	(83)	(1.3)	
Age 30–34	-52	73 **	13	34	0.5	335
	(55)	(36)	(10)	(62)	(1.4)	
Age 35–39	-87	68 *	20 **	0	-0.7	-5
	(59)	(41)	(9)	(60)	(1.1)	
Age 40–44	-113 *	66 *	20 **	-27	-0.8	-245
	(61)	(40)	(9)	(62)	(1.1)	
Age 45–49	-122 *	48	8	-66	-1.0	-527
	(68)	(42)	(10)	(64)	(1.0)	

Table 11., continued

	Impact on annual crude (all-cause) mortality rate										
	Days <10°C		Days 10°-30°C		Days >30°C		Total impact		% Change in rate		Years-life lost
	(1)		(2)		(3)		(4)		(5)		(6)
Age 50–54	-158	**	49		12		-97		-1.0		-532
	(70)		(43)		(11)		(66)		(0.9)		
Age 55–59	-145	**	73		24	**	-48		-0.2		-33
	(74)		(46)		(11)		(73)		(0.8)		
Age 60–64	-159	*	50		35	***	-74		-0.5		-84
	96		(55)		(13)		(91)		(0.8)		
Age 65–69	-272	**	93		41	***	-138		-0.7		-124
	(112)		(59)		(15)		(96)		(0.7)		
Age 70–74	-175		195	***	66	***	86		1.0		60
	(123)		(65)		(16)		(105)		(0.7)		
Age 75+	-1354	***	339		116	***	-899	***	-1.3	**	-416
	(421)		(206)		(42)		(316)		(0.6)		
All ages	-3257	**	1885	**	622	***	-750		-0.3		36,056
(weighted)	(1519)		(935)		(207)		(1478)		0.8		

Note: The mortality rate is the annual number of deaths in a given age group per the population in that age group (expressed per 100,000.) Estimates based on error-corrected Hadley CM3 A1FI model. Temperature exposure is modeled with 11 temperature-day ranges defined as the number of days in a given temperature category in a municipality-year. Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by total municipal population within each age group. Age-group specific estimates were combined into an age-adjusted pooled estimate by taking a weighted average of the age-specific estimates, where the weight is the average population in each age group. Huber-White standard errors in parentheses, taking climate-change predictions as constants. Years of life lost based on the author's period life table for Mexico, with discounting and age-weighting. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 12. Estimates of the Impact of Mid-Century Climate Change on Annual (All-Cause) Mortality Rate, by Age Group and Segment of the Future Temperature Distribution

	Impact on annual crude (all-cause) mortality rate					
	Days <10°C	Days 10°-30°C	Days >30°C	Total impact	% Change in m. rate	Years-life lost
	(1)	(2)	(3)	(4)	(5)	(6)
2040-2069						
Age 0–4	-431 *	1164 ***	1852 ***	2585 ***	9.5 **	779,172
	(224)	(440)	(237)	(607)	(3.7)	
Age 5–9	-7	55	50	98	7.0	25,586
	(17)	(41)	(33)	(67)	(4.8)	
Age 10–14	-24	17	78 **	71	4.7	12,675
	(17)	(38)	(33)	(64)	(4.3)	
Age 15–19	-57	33	81	57	4.3	8,561
	(35)	(72)	(56)	(110)	(4.0)	
Age 20–24	-103 **	-31	-15	-149	-0.7	-3,195
	(50)	(89)	(73)	(139)	(3.3)	
Age 25–29	-67	-78	267 ***	122	3.6	11,027
	(78)	(125)	(96)	(214)	(3.3)	
Age 30–34	-58	87	111	141	2.7	7,344
	(61)	(98)	(82)	(155)	(3.2)	
Age 35–39	-96	-2	168 **	69	0.1	109
	(65)	(102)	(76)	(150)	(2.7)	
Age 40–44	-125 *	35	173 **	82	0.2	184
	(67)	(107)	(79)	(153)	(2.6)	
Age 45–49	-136 *	84	73	21	-0.3	-50
	(75)	(113)	(86)	(159)	(2.2)	

Table 12., continued

	Impact on annual crude (all-cause) mortality rate										
	Days <10°C		Days 10°-30°C		Days >30°C		Total impact		% Change in m. rate		Years-life lost
	(1)		(2)		(3)		(4)		(5)		(6)
Age 50–54	-175	**	13		106		-56		-0.7		-214
	(78)		(113)		(100)		(169)		(2.1)		
Age 55–59	-161		78		212		129		-0.6		-265
	(82)		(128)		(102)		(182)		(2.0)		
Age 60–64	-176	*	-7		305	***	122		0.7		191
	(107)		(151)		(113)		(209)		1.9		
Age 65–69	-301	**	8		349	***	56		0.8		57
	(129)		(160)		(127)		(218)		(1.7)		
Age 70–74	-194		417	**	574	***	797	***	5.8	***	3,097
	(136)		(171)		(137)		(238)		(1.6)		
Age 75+	-1490	***	211		1023	***	-266		-0.1		-9
	(466)		(513)		(369)		(611)		(1.2)		
All ages	-3612	**	2084		5407	***	3878		3.9	**	844,270
(weighted)	(1685)		(2463)		(1800)		(3446)		(1.7)		

Note: The mortality rate is the annual number of deaths in a given age group per the population in that age group (expressed per 100,000.) Estimates based on error-corrected Hadley CM3 A1FI model. Temperature exposure is modeled with 11 temperature-day ranges defined as the number of days in a given temperature category in a municipality-year. Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by total municipal population within each age group. Age-group specific estimates were combined into an age-adjusted pooled estimate by taking a weighted average of the age-specific estimates, where the weight is the average population in each age group. Huber-White standard errors in parentheses, taking climate-change predictions as constants. Years of life lost based on the author's period life table for Mexico, with discounting and age-weighting. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 13. Estimates of the Impact of End-of-Century Climate Change on Annual (All-Cause) Mortality Rate, by Age Group and Segment of the Future Temperature Distribution

	Impact on annual crude (all-cause) mortality rate										
	Days <10°C		Days 10°-30°C		Days >30°C		Total impact		% Change in m. rate		Years-life lost
	(1)		(2)		(3)		(4)		(5)		(6)
2070-2099											
Age 0–4	-437	*	1592	***	4065	***	5221	***	19.3	***	2,934,497
	(227)		(605)		(521)		(959)		(6.1)		
Age 5–9	-7		27		110		130		10.3		48,448
	(18)		(64)		(73)		(113)		(8.1)		
Age 10–14	-25		5		172	**	152		9.1		50,420
	(17)		(59)		(73)		(111)		(7.6)		
Age 15–19	-58		29		177		148		7.2		36,215
	(36)		(108)		(123)		(183)		(6.1)		
Age 20–24	-104	**	-143		-32		-279		-2.4		20,867
	(50)		(132)		(157)		(231)		(5.3)		
Age 25–29	-68		-181		575	***	327		7.6		55,903
	(79)		(184)		(207)		(356)		(5.5)		
Age 30–34	-58		39		-238		218		3.9		16,212
	(62)		(144)		(175)		(263)		(5.2)		
Age 35–39	-98		-106		-359	**	155		0.2		491
	(66)		(147)		(162)		(248)		(4.4)		
Age 40–44	-127	*	10		369	**	252		0.9		2,522
	(68)		(150)		(168)		(250)		(4.1)		
Age 45–49	-138	*	123		157		142		0.3		335
	(76)		(163)		(184)		(265)		(3.6)		

Table 13., continued

	Impact on annual crude (all-cause) mortality rate										
	Days <10°C		Days 10°-30°C		Days >30°C		Total impact		% Change in m. rate		Years-life lost
	(1)		(2)		(3)		(4)		(5)		(6)
Age 50–54	-177	**	38		227		88		0.0		1
	(78)		(162)		(214)		(291)		(3.4)		
Age 55–59	-163	**	120		455	**	412		1.6		2,205
	(83)		(183)		(219)		(296)		(3.1)		
Age 60–64	-179	*	-59		659	***	421		1.7		1,582
	(108)		(215)		(243)		(333)		(2.9)		
Age 65–69	-305	**	-125		751	***	320		1.9		761
	(126)		(236)		(274)		(355)		(2.6)		
Age 70–74	-196		647	***	1238	***	1689	***	11.0	***	11,865
	(138)		(245)		(296)		(391)		(2.6)		
Age 75+	-1518	***	-84		2208	***	605		1.4		293
	(472)		(698)		(797)		(975)		(1.9)		
All ages	-3658	**	1933		11726	***	10001	*	8.9	***	3,182,617
(weighted)	(1707)		(3496)		(3888)		(5621)		(2.4)		

Note: The mortality rate is the annual number of deaths in a given age group per the population in that age group (expressed per 100,000.) Estimates based on error-corrected Hadley CM3 A1FI model. Temperature exposure is modeled with 11 temperature-day ranges defined as the number of days in a given temperature category in a municipality-year. Regressions include municipality fixed-effects, time fixed-effects and quadratic regional time trends. All statistics are weighted by total municipal population within each age group. Age-group specific estimates were combined into an age-adjusted pooled estimate by taking a weighted average of the age-specific estimates, where the weight is the average population in each age group. Huber-White standard errors in parentheses, taking climate-change predictions as constants. Years of life lost based on the author's period life table for Mexico, with discounting and age-weighting. * significant at 10%; ** significant at 5%; *** significant at 1%.

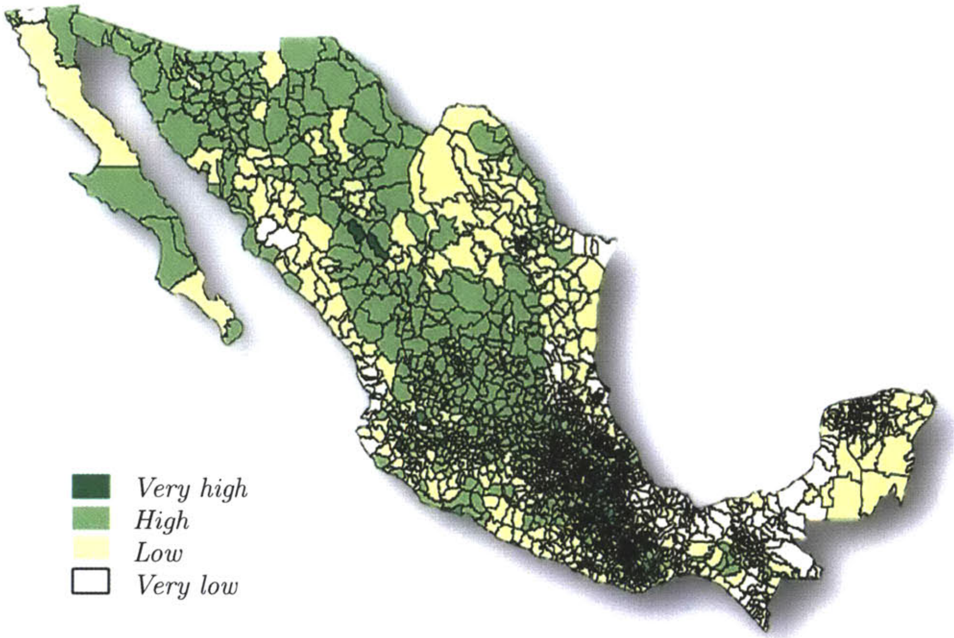

Figure 1. Vulnerability intensification due to climate change, by municipality, 2005-2045
Source: Borja-Vega and De la Fuente (2013)

Figure 2. The Mexican mesoregions

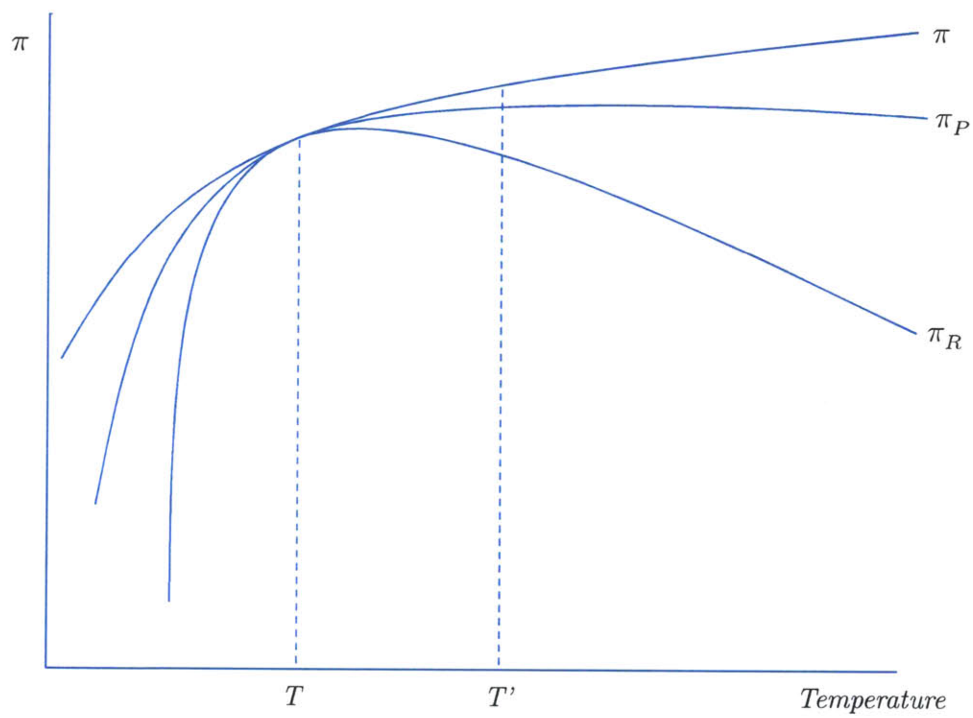

Figure 3. True impact of climate change on the utility of the household and estimated impacts based on the Ricardian and panel-data approaches, which differ on their adaptive behavior assumptions

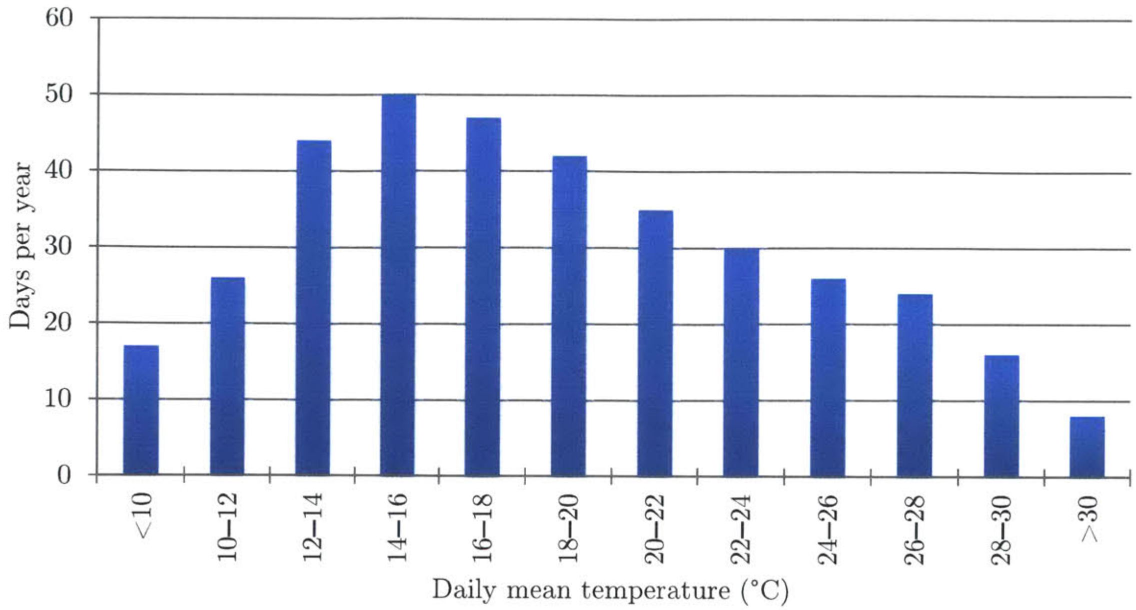

Figure 4. Temperature distribution in Mexico, 1979-2010

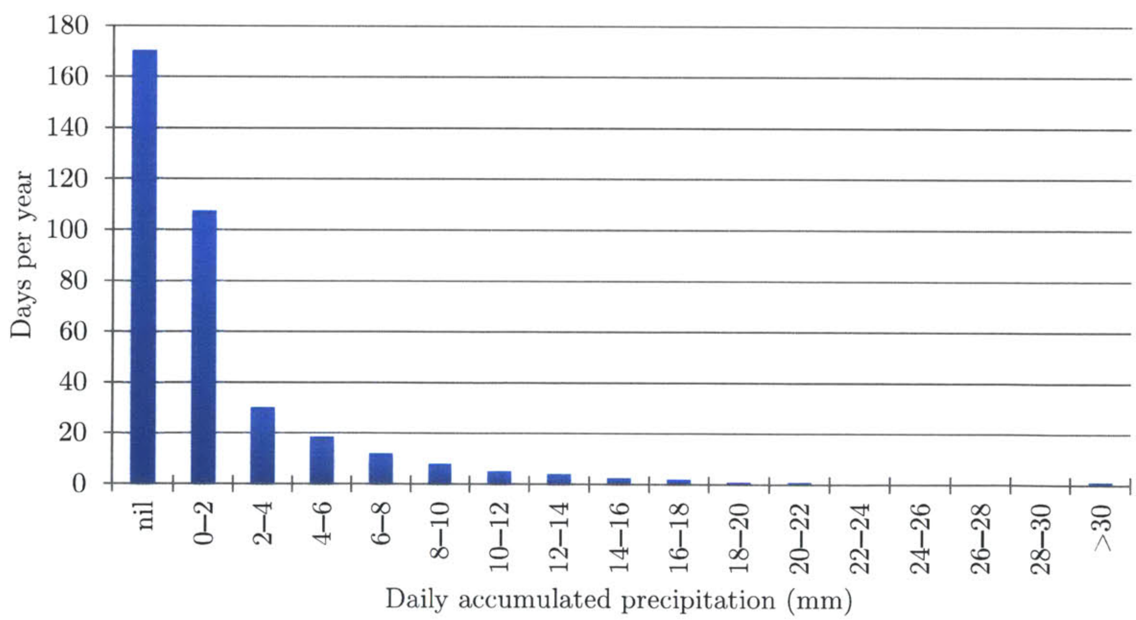

Figure 5. Rainfall distribution in Mexico, 1979-2010

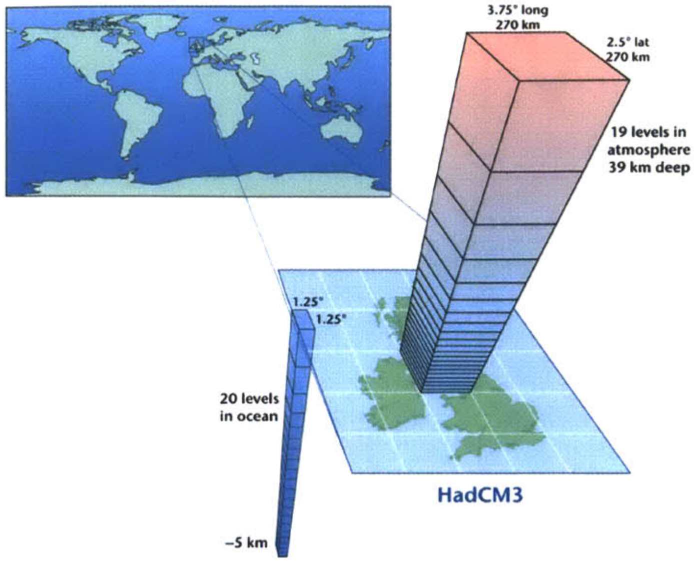

Figure 6. The horizontal and vertical structure of the HadCM3 climate model
Source: UK Climate Projections.

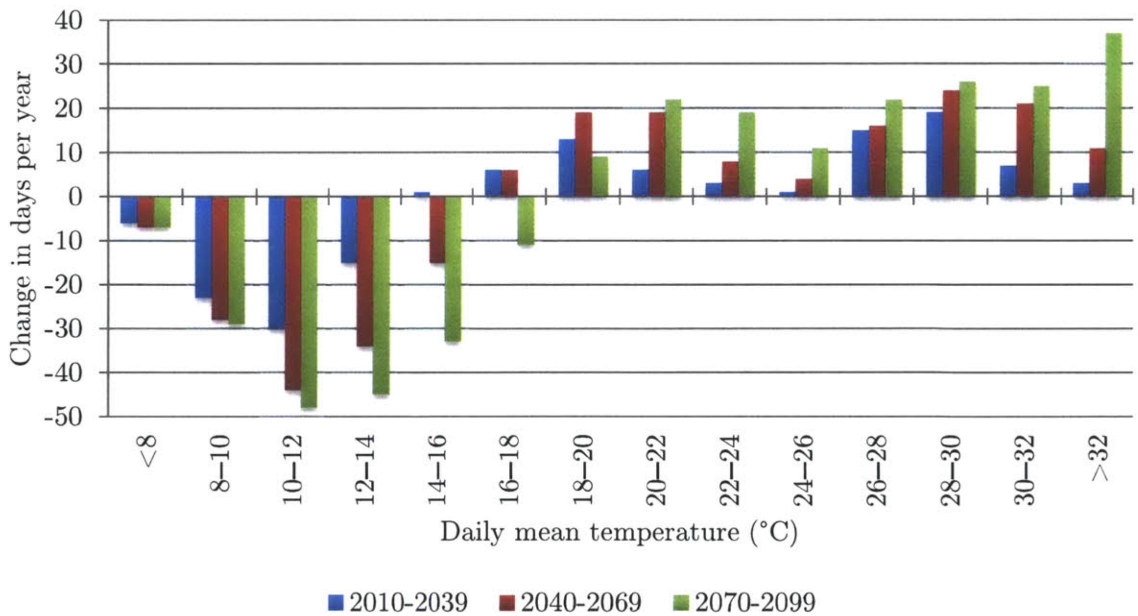

Figure 7. Predicted change in the distribution of daily temperatures (in °C) in Mexico, by period, according to error-corrected HadCM3 A1FI greenhouse gas emissions scenario

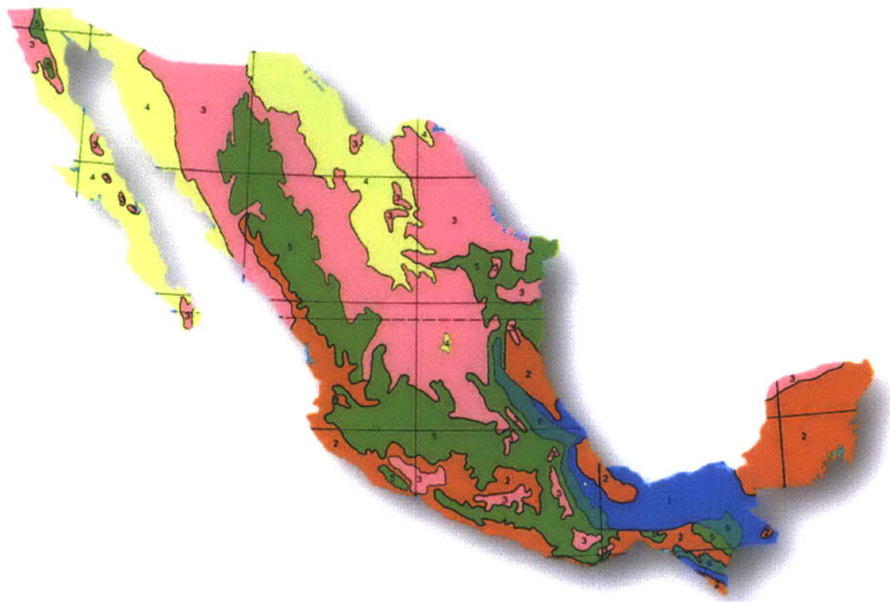

Figure 8. Weather in Mexico, by climate group
Notes: Group 1: Tropical humid climate; Group 2: Tropical sub-humid climate; Group 3: Dry climate; Group 4: Very dry climate; Group 5: Temperate sub-humid climate; Group 6: Temperate humid climate.
Source: Instituto Nacional de Estadística, Geografía e Informática.

Chapter 3

Climate Shocks, Safety Nets, and Shielded Poor: Experimental Evidence from Rural Mexico[†]

1 Introduction

Weather has become more extreme. It has become hotter: since 2000, at least 59 countries and territories, along with the South Pole, have had their highest temperature records broken (Weather Underground 2012, United States Antarctic Program 2012), with over half of these record-breakers taking place over the past 36 months.[21] Weather has become colder too: during the same time period, at least 10 countries recorded all-time low temperatures, according to the same sources.[22] It has also become rainier: globally, 2010 and 2011 have been the years with the heaviest documented rainfall in more than a century of recordkeeping (National Oceanic and Atmospheric Administra-

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[21] These countries and territories are Afghanistan, Algeria, Anguilla, Armenia, Aruba, Ascension Island, Bahrain, Belarus, Bosnia and Herzegovina, Cape Verde, Cayman Islands, Chad, China, Colombia, Congo-Brazzaville, Cyprus, Dominica, Dominican Republic, Finland, France, French Guiana, Gabon, Germany, Guinea, Indonesia, Iran, Iraq, Japan, Jordan, Kenya, Kuwait, Luxembourg, Macau, Micronesia (FSM), Moldova, Morocco, Myanmar, Niger, Nigeria, Norfolk Island, Palau, Pakistan, Portugal, Russia, Rwanda, Saudi Arabia, Somalia, Switzerland, Sudan, Tanzania, Tunisia, Turkey, Turks and Caicos Islands, Ukraine, the United Arab Emirates, the United Kingdom, the United States, Zambia, and Zimbabwe. The India Meteorological Department doubts the validity of 55°C (131°F) readings reported in Orissa during 2005.

[22] These countries are Bhutan, Chile, Egypt, Ethiopia, Guinea, Guyana, Niue, Tuvalu, the United Arab Emirates, and the United Kingdom.

tion 2011.) It has become drier as well: only in Mexico, nearly 900,000 hectares of farmland and 1.7 million head of livestock have been lost due to severe drought – the worst in more than seven decades of data collecting. April 2011 was the first time on record where more than 95% of the country was considered to be undergoing drought, according to the North American Drought Monitor (National Commission of Water 2012.) Min et al. (2011) and Pall et al. (2011) attribute this extreme weather trend to anthropogenic climate change. To the extent that global warming intensifies, climate extremes are likely to be more recurrent in the future, as discussed in an article by Easterling et al. (2000.) Abrupt weather has multiple environmental, social, and economic repercussions.

In this paper, I argue that extreme weather phenomena hit one specific group of people disproportionately and unfairly: the poorest of the poor. As I will discuss below, this is because not only does weather impacts the very things the poorest depend on most –dry-land agriculture; tropical forests; and subsistence fishing (Deschênes & Greenstone 2006)– but also because the very poor are not able to access credit, savings and insurance markets, or other traditional and institutional social-risk management instruments to cope with the adverse effects of unexpected shocks, like severe weather (Banerjee 2004, Banerjee & Duflo 2007, Global Humanitarian Forum 2009, Lee 2009, Mendelsohn 2009.) The World Bank (2010) reports that the demand for agricultural insurance is usually low or even nonexistent where formal credit is not available for agriculture. Mexico is no exception: while the private sector's participation in agricultural insurance has been oriented toward developed agricultural regions and large or very well organized producers, low-income agricultural producers do not have access to insurance, and rely on agricultural producer associations or government-sponsored insurance in the wake of extreme weather events (Centro de Estudios de las Finanzas Públicas 2011, Villarreal González 2009.) Overall, more than one in three municipalities in Mexico do not have access to crop insurance provided by the government, as Figure 1 illustrates. Not surprisingly, recovery after a climate shock is slow or simply impossible as a result: Figure 2 shows that of the 278 major natural disasters that have taken place in Mexico between 1980 and 2010, insured losses accounted for only 5 billion USD of the 31 billion USD damage.

In open economies, like Mexico's, the vulnerability of the poor is further exacerbated by the negative consequences of globalization, particularly the marginalization of production (O'Brien & Leichenko 2000.) This is evident by taking a look at Figures 3 and 4, which together show a clear overlap between vulnerability and poverty, whose interplay has been the subject of rigorous study (Eakin 2005, Eriksen et al. 2007) I argue in this paper that the dominance of economic uncertainty over environmental risk in households' decisions implies a continued role for government intervention to help households adapt to climatic stress.

The objective of this paper is normative in nature. My interest is to show that, in the absence of these mechanisms, alternative interventions may be effective to mitigate the negative impact of weather-induced income shocks. In particular, I investigate the extent to which anti-poverty programs increase welfare by reducing vulnerability and enhancing consumption smoothing, as proposed in the social risk management literature (see Holzmann & Jørgensen (2000) for a review.) It is argued that enhancing the ability of households and communities to deal with climatic variability and risks is beneficial (IPCC 2012), yet the extent to which enhanced coping capacities lead to improvements in welfare is not clear. Such knowledge is much needed at a time when there is pressure to cut social development programs that give people the chance to lead healthier and more productive lives.

In general, the question of whether anti-poverty programs are effective vulnerability-reduction mechanisms is of paramount importance for developing countries seeking to incorporate climatic risk considerations in future development initiatives. However, in order to answer it empirically, an important methodological problem needs to be overcome: program recipience is not random. By definition, anti-poverty programs are implemented in poor communities and, as a result, vulnerability may be higher in the areas where the program operates. Observational analyses might confound the effect of the program with the economic, behavioral and political institutions that hinder development in the first place. Without an identification strategy, the researcher could only establish a correlation between policies and vulnerability outcomes at best.

2 Objective and Contributions

I contribute to this debate by assessing the impact on poor rural Mexican households of extreme temperature and precipitation induced by El Niño and La Niña, climate patterns characterized by anomalous sea surface temperature that exacerbates the incidence of severe weather phenomena. I rely on exogenous variation in recipience in order to evaluate the extent to which a large antipoverty program mitigates climate vulnerability by comparing several welfare and consumption outcomes between program recipients and non-recipients.

This paper is innovative because I combine high-resolution daily climatic data at the community level from a long-term, high frequency, dynamically consistent meteorological model with survey data for 24,000 households in 506 Mexican communities in seven states of Mexico (Guerrero, Hidalgo, Michoacán, Puebla, Querétaro, San Luis Potosí, and Veracruz.) The survey was part of the original impact evaluation of the National Program of Education, Health, and Nutrition (which I will henceforth refer to as Progresa, as is typically known in Mexico), a conditional cash-transfer program designed to increase school attendance and doctor visits. My identification strategy draws on the fact that Progresa began to operate randomly in 320 communities in May 1998, but had not been implemented in other 186 communities by December 1999. This phased rollout introduced random assignment. As Levy (2006, p. 37) points out and is graphically shown in Figure 5, "the first set of localities and families could be considered subject to the effects of the program and the second set representative of what happens in the absence of the program (until they are incorporated); in other terms, the first set would be the treatment group and the second the control group." These two groups are probabilistically similar to each other in expectation. Hence, any outcome differences that are observed between those groups at the end of the study are likely to be due to the effect of Progresa, not to differences between the groups that already existed at the start of the study (Shadish, Cook, & Campbell 2002, p. 13.) The Progresa intervention is an example of a "randomized experiment," and provides a logical basis for making unbiased inferences about the causal impact of any given policy (Murnane & Willett 2010.)[23]

I present evidence on the disproportionately negative impact of weather shocks on the poor. Unlike previous empirical studies that focus on one class of shock, such as extreme temperature (Burgess et al. 2011, Deschênes & Moretti 2009), or extreme precipitation patterns (Aguilar and Vicarelli 2011), I analyze simultaneously four types of weather shocks: extreme heat, extreme cold, extreme rainfall, and extreme drought. The distinction is relevant because, as Hegerl, Hanlon and Beierkuhnlein (2011) argue, it is often not clear which extremes matter the most. I show that, in the event of most of these weather shocks, Progresa mitigates this inequality and partially insulates the poor from drastic contractions in income. I analyze the extent to which households receiving the benefits of the program use Progresa as a short-run consumption insurance mechanism. I measure consumption both in monetary and caloric terms, in order to assess whether poor households that face weather shocks self-insulate by acquiring relatively cheaper sources of calories, as reported by Behrman & Deolalikar (1989.) Similarly, I study other several self-insurance strategies to which households resort in the event of a weather-induced income shock. A self-insurance strategy that deserves special attention, given that deteriorating environments triggered by severe weather causes forced displacement of people, is migration (Piguet, Pécoud & de Guchteneire 2011.) I evaluate the extent to which Progresa provides a safety net that may reduce the propensity to migrate, thus avoiding costly *ex post* risk strategies that could compromise social and economic welfare. Finally, I analyze whether there are differences in household vulnerability by observable characteristics, such as the gender of the head of the household, his/her level of education and indigeneity or ethnic minority self-identification, and land tenure.

[23] This is why randomized controlled trials are often deemed as "the simplest and best way of assessing the impact of a program" (Banerjee, 2007, p. 5) because the researcher has "control over the treatment, [which] allow for the straightforward maintenance of the independence assumption" (Morgan & Winship 2007, p. 41), which presumes that treatment status is independent of the potential outcomes. I will discuss this in more detail when I present the theoretical framework of this paper.

I exploit the fact that, coincidentally, due to their time of occurrence, El Niño- and La Niña-induced extreme climatic events that took place in Mexico at the end of the 1990s were captured by the Progresa randomized evaluation data: the Climate Report for 1998 published by the American Meteorological Society (Bell et al. 1999) indicates that the period of July 1997 through June 1998, was unusually hot and the driest in the historical record for Mexico dating back to 1945. This drought was linked to the 1997-98 El Niño, the strongest El Niño event of the past century (Bell et al. 1999) (See Figure 6, Panels A and B.) In October 1998, a Progresa evaluation survey collecting information on events that took place in the previous year was carried out.

Similarly, a 2-year La Niña event suddenly started to develop in the spring of 1998 (see Figure 6, Panel C.) As a consequence, during the harvest season of September 1998 and especially that of October 1999, some areas experienced anomalous temperatures and unexpectedly intense rains and even floods. Then in November 1999, another Progresa evaluation survey was conducted. The parallel timing of the Progresa survey implementation and the occurrence of these extreme-weather events, along with the substantial variation in temperature and precipitation across communities, provides the unusual opportunity to make use of the program's randomized social-experiment component as a causal inference design to test whether the program successfully reduces climate vulnerability among the poor.

An important contribution of this paper is the use of daily climatic data, a significant improvement over the majority of studies that employ monthly or even yearly data to assess weather impacts (see for instance Aguilar & Vicarelli (2011), Sáenz Romero et al. (2010), and Pollak & Corbett (1993.)) The underlying shortcoming of these and other works that follow similar methodologies is that using monthly climatic data ignores the nonlinear effects of weather, which may be concealed when, for example, daily observations are averaged into monthly or seasonal variables, thus attenuating the impact of climate as a result. Deschênes and Greenstone (2011) and Schlenker and Roberts (2009) show that daily and finer-scale weather data facilitate the identification of nonlinearities and breakpoints in the effect of weather in empirical models.

This study benefits from studying the case of Mexican rural households for four reasons: first, the focus of most previous empirical climate-impact studies has been on the United States (Guiteras, 2008), but vulnerability to extreme weather is greater in the developing world, where agriculture typically plays a larger economic role. The Mexican case is ideal to evaluate the impact of weather variability in the context of resilient poverty. Second, Mexico represents a useful case to study the impact of extreme weather for developing countries, given that it has undergone diverse degrees of climate variability (e.g. extreme rainfall with La Niña event in 1999 and severe droughts as a result of the 1997-1998 El Niño effect) and that such phenomena are expected to become more recurrent (United Nations 2011.) Third, rural households in Mexico will be particularly affected by extreme-weather events derived from climate change. The Global Humanitarian Forum (2009) specifically underscores that Mexico is one of the most vulnerable regions to climate change, especially because of floods and increased rainfall variability. Similarly, the World Bank (2009) places Mexico among the countries most vulnerable to climate change: 68% of its population and 71% of its GDP are at risk of suffering the adverse consequences of this environmental phenomenon. Ethnographic data collected in agricultural communities in rural Mexico show that constraints in soil quality, topography and water resources make rural households in Mexico extremely sensitive to climatic conditions (Eakin 2006.) Fourth, in terms of my empirical analysis and as I will discuss in more detail when I present the methodology I employ for this paper, studying Mexico provides the unusual opportunity of using a national-scale data set created to evaluate a social policy in combination with climatic data in order to empirically analyze the impact of weather variability. In effect, the link between extreme-weather shocks and well-being usually has not been tested empirically. In fact, with the exception of the large-scale study by Burgess et al. (2009) and others thence derived, the research on the impact of inter-annual variation in weather on household behavior in developing countries is limited to anecdotal evidence and several relevant case studies that are nonetheless constrained by data unavailability. As far as I know, I am the first to examine empirically the impact of a social program as a weather-risk-mitigation mechanism, combining data from a randomized evaluation with information derived from sophisticated climate models.

The remainder of this paper is organized as follows: in Section 3, I present a review of the literature on the linkages between weather and development, and how severe climate and other types of unexpected income shocks in general, may decrease the welfare of the household in the absence of critical markets. In section 4, I discuss my conceptual framework of the impact of income shocks, deriving welfare gains from the provision of a safety net when private insurance markets are incomplete. Section 5 presents a detailed description of the data, while in Sections 6 and 7, I discuss the empirical specification I employed to analyze the impact of weather on welfare outcomes and evaluate the effectiveness of Progresa as a climate vulnerability mitigation mechanism and show the results. Section 8 provides a conclusion, summarizing the main findings.

3 A Synthesis of the Literature on Risk and the Poor

Extreme weather is an environmental phenomenon in essence, so it is logical that, at least comparatively, its ecological dimension has been the most comprehensively studied. However, the emphasis on ecosystem and biodiversity issues has relegated social and cultural phenomena to secondary concerns (Global Humanitarian Forum 2009.) Among the top 20 most-cited papers on climate and/or global warming published between 1999 and 2009, none of them investigates potential disruptions at the socioeconomic scale (Thomson Reuters 2009.) Among the most studied topics related to climate in recent years are its effect on ecosystem trajectories and ecological change (Parmesan & Yohe 2002, Walther et al. 2002); extinction risks and the evolutions, distributions and abundances of species (Hoegh-Guldberg 1999, Root et al. 2003, Thomas et al. 2004); feedbacks in the climate system (Cox et al. 2000, Roeckner et al. 1999); and the vulnerability of natural resources (Vorosmarty et al. 2000.)

In spite of the research imbalance, significant work has been done on the many forms extreme weather affects people and their standard of living. Deschênes and Moretti (2009) and McMichael et al. (2006) find that abrupt climate is associated with diminished health condition and increased temporal displacement. Rosenzweig et al. (2001) focus on the effect of extreme weather events on agriculture and food production, showing that shifts in climate will disproportionately affect developing countries, exposing them to reduced food supplies and potential increases in malnutrition. In rural regions, extreme weather may result in microecological adjustments such as mulch application and tillage alterations (Wilken 1987), crop diversification (Altieri & Trujillo 1987, Trujillo 1990), geographical relocation of agricultural production (Thompson & Wilson 1994), and assets sell (such as livestock and farm equipment) (Eakin 2000.) Endfield (2007) explores how extreme weather events drove community engagement and the creation of social networks as a means of fortifying social resilience, taking colonial Mexico as her case study. Burgess et al. (2011) document a large effect of weather on death among India's rural population, respectively, stemming from the fact that this population's economic welfare is almost entirely drawn from agricultural income streams. In all, as Binswanger and Rosenzweig (1993) claim, weather is the factor contributing to income variability that is most likely to influence welfare, particularly in agricultural economies.

If extreme weather is understood as an unexpected income shock, with a generally negative impact on the household's income stream, it is likely that it will affect groups whose income is low. For one, as I document in Guerrero Compeán (2013), extreme weather affects households living in poverty disproportionately given that adverse climatic events impact agricultural productivity and crop yields, thus drastically reducing household income. Particularly in the short run, given their inability to adapt to unexpected shocks, farmers' incomes are particularly uncertain and vulnerable to the increased frequency and severity of adverse climatic events (LaFleur, Purvis & Jones 2009.) One reason why poor households are seldom able to cope with the negative effects of weather shocks is that they rarely have access to formal *ex ante* risk management and *ex post* risk coping instruments provided by the savings, credit and insurance markets to face a negative income shock, either because they do not exist or because they work imperfectly as a result of the borrower's limited liability and other standard problems of moral hazard and adverse selection (Bell 1988, Besley 1994, Stiglitz 1990.) The poor are thus left with a variety of alternative mechanisms that provide inadequate insurance at a very high cost for the household. Simply put, in the absence of savings, credit, or insurance mechanisms, adverse climatic events are likely to cause fluctuations in rural household incomes, which in turn will lead to negative changes in household consumption, posing serious consequences for the wellbeing of farmers in a village economy (Paxson 1992, Townsend 1994.)

The many channels through which households cope with the lack of well-developed insurance and credit markets and buffer themselves from the effects of risk have been the subject of a considerable body of theoretical and empirical work. Households can insulate themselves from the negative effects of an unexpected income shock through savings, income-smoothing or other risk management strategies, and a variety of informal risk-sharing mechanisms. These strategies are discussed below.

3.1 Self-Insurance through Asset Accumulation/Depletion

The basic self-insurance strategy employed by households to cope with risk is savings, or, more generally, asset holding. In particular, asset holding is traditionally hypothesized as another income shock buffer for poor households in the context of imperfect credit markets (Deaton 1991, 1992.) The consumer builds up assets in good years to deplete in bad years, i.e., saves and dissaves, in order to smooth consumption in the face of income uncertainty. Using data from a nine-round survey conducted in northern Nigeria, Udry (1995) finds that, consistent with simple models of consumption smoothing, net saving is lower in those households subjected to adverse idiosyncratic shocks on their upland plots.

Binswanger and McIntire (1987) and Davies (1996) argue that buying and selling cattle is a traditional strategy to cope with income fluctuations in many rural areas. Rosenzweig and Wolpin (1993) have shown that bullock sales contribute to consumption smoothing in South Indian villages, although Lim and Townsend (1994) argue that crop inventory appears to be the main strategy.

Asset accumulation is not risk-free however. Dercon (2002) discusses that during the Ethiopian famine in the 1980s, the terms of trade between livestock and staples were severely distorted, so that farmers needed to raise three times as much livestock to purchase the same amount of food, drastically reducing consumption instead of selling assets as a result. Similarly, Hoogeveen (2002) finds that livestock sales are ineffective income shock buffers. Fafchamps, Udry and Czukas (1998) show that during some of the worst drought years in Burkina Faso's recent history, livestock sales compensated for at most between 15% and 30% of income fluctuations.

3.2 Self-Insurance through Income and Consumption Smoothing

Households also resort to strategies that reduce risk in the income process, usually in the form of conservative allocation portfolios and income diversification. Eswaran and Kotwal (1989) show that, unlike households without liquidity constraints, asset-poor households in an imperfect credit market are not able to carry out activities whose income is volatile, given that risk is high.

To handle income risk, asset-poor households will have to enter suboptimal low-risk, low-return activities. Using data from Indian households, Murdoch (1990, 1995) illustrates that asset-poor households sacrifice expected profits for lower risk, devoting a larger share of land to safer traditional varieties of rice and castor than to riskier but high-return varieties. Similarly, Binswanger & Rosenzweig (1993) study rural villages in South India and show that farmers shift production into more conservative and less profitable modes as the environment becomes riskier.

Kochar (1995) argues that another income-based strategy to cope with risk is for households to adjust labor supply. Taking India as a case study, he finds that households are fairly insulated from crop shocks due to well-functioning labor markets, which enable them to smooth shocks through compensating increases in market hours of work.

Alderman and Paxson (1994) and Barrett, Reardon and Webb (2001) document that income source diversification is another form of self-insurance when credit and insurance markets fail. Webb and Reardon (1992) find that households' capacity to cope with the drought shocks of the mid-1980s in Burkina Faso were strongly associated with the extent of their non-farm diversification patterns. Barrett and Arcese (1998) similarly show that wildlife poaching in Tanzania in part responds to agroclimatic shocks that affect farm labor productivity. Townsend (1993) demonstrates that *ex ante* spatial land fragmentation for crop diversification has been a mechanism used since medieval times to reduce risk from yield variability. Carter (1997) further discusses the issue of diversification and argues that intercropping two crops, such as moisture-intensive sorghum and moisture-extensive millet, on the same field is common practice in West African agriculture to diversify against specific, microclimatic risk.

In an extreme situation, Miguel (2005) reports that severe weather events lead to a large increase in the murder of elderly women ("witches") by relatives in a rural Tanzanian district. A hypothesis is that households near subsistence consumption levels kill, expel, or starve relatively unproductive elderly household members to safeguard (i.e., consumption-smooth) the nutritional status of other more productive members. Chen (2007) develops a model of religiously motivated social violence, inspired by the rise of Islamic fundamentalism during the Indonesian financial crisis. He shows that the need for *ex post* insurance resulting from economic distress stimulates individuals to join religious clubs that have a consumption-insurance function, and where commitment to the group can be demonstrated by taking violent actions against non-group members. He finds that credit availability mitigates the effect of economic distress on violence.

As in the case of self-insurance through asset accumulation, income-smoothing strategies are, however, partially effective in terms of risk reduction. Duflo and Udry (2004) show that household members may not to insure each other against variation in income that they can perfectly observe. Sen (1981) and Fafchamps, Udry and Czukas (1998) discuss that natural disasters may decrease the demand for local services, diminishing the effectiveness of income source diversification. Similarly, specialization may not imply that households are risk-takers, but rather that they do not have the option to diversify: in general, non-agricultural, non-exploitative activities or lucrative alternative agricultural activities are not easily accessible to the poor (Dercon 2002), especially poor women (Kabeer 1990), as a result of household characteristics (Bigsten & Kayizzi-Mugerwa 1995), institutional, economic and cultural conditions (Heyer 1996, Jiggins 1986, Watts 1988) as well as differences in timing and location of activities, or a capacity to estimate risks (Adams & Mortimore 1997, Evans & Ngau 1991.) The implication is that the poor have to enter into low return-capital extensive activities, since high return activities require capital. As a result, they are less diversified despite facing more serious consequences of bad income draws with limited insurance and credit market imperfections. In all, many diversification strategies are actually mean income reducing, making them less interesting for households (Dercon 2002.)

3.3 Self-Insurance through Informal Risk-Sharing

The implications of risk sharing, defined as sharing with another party the burden of loss from a risk and the measures to reduce such risk, have been studied both from the theoretical modeling and empirical research standpoints (Coate & Ravallion 1993, Nash 1966, Ligon, Thomas & Worrall 1997, Kimball 1988, Townsend 1994, Jacoby & Skoufias 1998.)

Grimard (1997) evidences partial insurance performed by individual households with other members of the same ethnic group in Côte d'Ivoire, particularly for the households residing in the regions least likely to have access to formal financial arrangements. In a relevant study, Udry (1994) finds that informal mutual insurance cannot insure people completely. He documents that increases in risk make insurance less effective by reducing the maximum enforceable group size, while finding that almost no borrower defaulted when they faced a negative shock. Conversely, defaults were more frequent when the borrower benefited from a positive shock, suggesting that the terms of repayment are endogenously adapted in the event of a negative shock. In addition, as first suggested by Becker (1974), Udry shows that informal mutual insurance is similar to state-contingent credit or quasi-credit arrangements: on average a borrower with a good realization repays *more* than s/he borrowed but a borrower with a bad realization repays *less*. Likewise, a lender with a good realization receives on average *less* than s/he lent, but a lender with a bad realization receives *more*.

The literature provides evidence that households engage in risk-sharing strategies aimed at insulating, at least partially, consumption changes from income changes. Rosenzweig (1988) shows that, in the absence of income insurance, cross-household kinship ties are a common risk-mitigation strategy, with families marrying daughters intentionally to grooms in distant villages as an implicit insurance-based transfer schemes which contributes to smoothing consumption through remittances in the face of income losses by any of the households involved. Fafchamps and Lund (2001) show that households dealing with negative shocks receive help through networks of friends and family in the form of gifts and informal loans. Controlling for income, Ravallion and Dearden (1988) find that in rural Java, households with ill members are recipients of greater transfers. Chen (2010) presents a theory of religion as a risk-sharing mechanism in which people pool their resources and redistribute the pool according to their relative religious intensities.

But risk-sharing arrangements are limited in their effectiveness. As Dercon (2002) argues, when households understand that they are part of a risk-sharing agreement, they will accumulate assets only to cope with common shocks to self-insure, given that idiosyncratic shocks could now be insured through the risk-sharing agreement. In more general terms, if savings are possible, then the introduction of a public safety net would reduce (or crowd-out) precautionary savings, since overall risk has been reduced, which by definition means lower precautionary savings (Deaton 1991, Cox & Jiménez 1992.) Household characteristics also determine the effectiveness of risk-sharing agreements. Using data for a Tanzanian village, De Weerdt (2002) shows that the poorer the household the smaller the social network they can rely on in times of need.

3.4 The Need for Safety Nets

Regardless of the risk-coping strategy, the overall conclusion of this research is that most households succeed in partially protecting themselves from the full effects of the income shocks to which they are subjected, but not to the degree required by either a Pareto efficient allocation of risk (within local communities) or by the permanent income hypothesis (over time) (Kazianga & Udry 2006.) A clear policy implication is that given the poor's lack of access to private credit and insurance markets, as well as the inadequacy of the informal risk-coping mechanisms they resort to in order to mitigate the adverse effects of unexpected income shocks, a state-provided safety net could yield substantial welfare gains. As implied by Diamond (1977), if the private market limits or does not provide access to credit and insurance to economic agents, a safety net could help alleviate this market failure. With this in mind, the next section presents a model of income shocks and derives the welfare gains from the provision of a safety net when private insurance markets are incomplete.

4 The Basic Model of Social Insurance for the Poor

The theoretical framework of this paper is an effort to show that the provision of safety nets has important consequences in terms of welfare for the poor. I adopt the social insurance model developed by Chetty and Looney (2006.) The model underlies the empirical analysis of the next section, and emerges from the public economics literature. It shows that the extent to which a safety net increases welfare is a function of the intensity of the shock and the degree of risk aversion of the household. One of the key predictions of the model is that the welfare value of insurance may be significant in the context of imperfectly functioning markets, where credit and insurance mechanisms are not readily available. Alternatively, insurance may be important in situations where high levels of risk aversion are typical, as costly *ex post* risk strategies that could compromise social and economic welfare are less likely to be relied upon.

Formally, given that the household's utility derived from consumption is expressed as $u(c)$, the disutility of attaining c dollars of consumption, i.e., the effort the household engages in to obtain such level of consumption, equals

$$\phi(c) = \theta(c) \tag{1}$$

The notion that a weather shock increases the value of θ should be straightforward: in the absence of a weather shock, θ represents the typical effort required by the household to consume c dollars. As I discussed in the review of the literature, given that the economic and social costs of *ex post* risk-coping, be it in the form of asset depletion, suboptimal portfolio choices, migration or otherwise, are oftentimes substantial, households need to put more effort in order to maintain the same level of consumption c, so that θ increases.

If the effort typically required to attain a level of consumption c is normalized to $\theta = 1$, in the event of a weather shock $\theta = 2$ if it takes twice as much effort to generate the same level of consumption.

Let p be the probability of the household being hit by a weather shock. c_s is the consumption level of the household in the event of a shock, while c_{ns} is the consumption level of the household in the absence of a shock, which are assumed to be different if households do not have complete access to the credit and insurance markets. An actuarially fair insurance program that rises c_s by one dollar must lower c_{ns} by $\frac{p}{1-p}$. The marginal welfare gain from such a program is expressed by

$$\widetilde{W} = pu'(c_s) - (1-p)\frac{p}{1-p}u'(c_{ns}) = p(u'(c_s) - u'(c_{ns})) \tag{2}$$

Cardinally, this expression is uninterpretable given that utility functions are not uniquely defined. In monetary terms, equation (2) may be expressed as the normalized gain from a one-dollar change in consumption in the absence of a shock, that is, $(1-p)u'(c_{ns})$. If p is fixed, the welfare gain from social insurance relative to an increase in consumption in the absence of a shock is then proportional to

$$W \propto \frac{u'(c_s) - u'(c_{ns})}{u'(c_{ns})} \tag{3}$$

For simplicity, one can obtain a second-order Taylor approximation to the change in social welfare:[24]

$$u'(c_s) \approx u'(c_{ns}) + u''(c_{ns})(c_s - c_{ns}) + \frac{1}{2}u'''(c_{ns})(c_s - c_{ns})^2$$

$$\Leftrightarrow \frac{u'(c_s) - u'(c_{ns})}{u'(c_{ns})} \approx \frac{u''(c_{ns})(c_s - c_{ns})}{u'(c_{ns})} + \frac{1}{2}\frac{u'''(c_{ns})(c_s - c_{ns})^2}{u'(c_{ns})}$$

$$= \frac{u''(c_{ns})}{u'(c_{ns})}(c_s - c_{ns}) + \frac{1}{2}\frac{u'''(c_{ns})}{u''(c_{ns})}\frac{u''(c_{ns})}{u'(c_{ns})}(c_s - c_{ns})^2$$

[24] Consider a differentiable real-valued function on some subset of Euclidean space, $f\colon \mathbb{R}^n \to \mathbb{R}$. The function can be approximated in the region around some arbitrary point $y \in \mathbb{R}^n$ by its tangent hyperplane. If $f\colon \mathbb{R}^n \to \mathbb{R}$, the Taylor approximation takes the form $f(x) \approx \sum_{k=0}^{n} \frac{f^{(k)}(y)}{k!}(x-y)^k = f(y) + f'(y)(x-y) + \frac{1}{2}f''(y)(x-y)^2 + \cdots$.

$$= -\frac{u''(c_{ns})}{u'(c_{ns})}(c_{ns} - c_s) + \frac{1}{2}\frac{u'''(c_{ns})}{u''(c_{ns})}\frac{u''(c_{ns})}{u'(c_{ns})}(c_{ns} - c_s)^2$$

$$= -\frac{u''(c_{ns})}{u'(c_{ns})}(c_{ns} - c_s) \cdot \frac{c_{ns}}{c_{ns}} + \frac{1}{2}\frac{u'''(c_{ns})}{u''(c_{ns})}\frac{u''(c_{ns})}{u'(c_{ns})}(c_{ns} - c_s)^2 \cdot \left(\frac{c_{ns}}{c_{ns}}\right)^2$$

Notice that $\gamma = -\frac{u''(c_{ns})}{u'(c_{ns})} \cdot c_{ns}$ is the Arrow-Pratt measure of relative risk-aversion (Arrow 1965, Pratt 1964), $\rho = -\frac{u'''(c_{ns})}{u''(c_{ns})} \cdot c_{ns}$ is the coefficient of relative prudence (Kimball 1990)[25], and $\frac{\Delta c}{c} = \frac{c_{ns}-c_s}{c_{ns}}$ is the decrease in consumption resulting from the weather shock. Hence,

$$W \backsimeq \gamma\frac{\Delta c}{c} + \frac{1}{2}\rho\gamma\left(\frac{\Delta c}{c}\right)^2 \tag{4}$$

If the third and higher order terms of $u(c_{ns})$ are small, i.e., $u'''^{(c_{ns})} \approx 0 \Rightarrow \rho \approx 0$, we arrive at

$$W \backsimeq \gamma\frac{\Delta c}{c} \tag{5}$$

As a result, the welfare gain of providing a safety net can be expressed as the product of the size of consumption fluctuations ($\frac{\Delta c}{c}$) and the utility value derived from exhibiting (the optimizing behavior of) a smoother consumption path (γ) over time. The empirical analysis of this paper provides an estimate of ($\frac{\Delta c}{c}$) for a variety of weather shocks.

Notice that even if consumption falls negligibly, the benefits of a safety need are significant if households are highly risk-averse, i.e., take costly measures to insure a smooth consumption path. Poor households, as argued in the review of the literature

[25] The coefficient of relative risk aversion measures the curvature (concavity) of the utility function. Similarly, the coefficient of relative prudence measures the curvature (convexity) of the marginal utility function. The greater the coefficient of relative prudence, the stronger is the precautionary savings motive.

above, incur substantial costs to avoid a decrease in their consumption patterns, given that they are by definition close to the subsistence level of consumption.

To formalize this notion, consider the isoelastic (constant relative risk-aversion) utility function

$$u(c) = \frac{c^{1-\gamma}}{1-\gamma} \tag{6}$$

where the elasticity of intertemporal substitution is the reciprocal of the Arrow-Pratt measure of risk aversion. Given the effort to attain the level of consumption c, the representative household chooses the optimal level of consumption c^*

$$\max_c \frac{c^{1-\gamma}}{1-\gamma} - \theta c \tag{7}$$

Hence

$$c^{*-\gamma} - \theta = 0 \Longrightarrow c(\theta) = \theta^{-\frac{1}{\gamma}} \tag{8}$$

A weather shock leads to a consumption fall equal to

$$\frac{\Delta c}{c} = \frac{c_{ns} - c_s}{c_{ns}} = 1 - \frac{c_s}{c_{ns}} = 1 - \left(\frac{1}{\theta_s}\right)^{\frac{1}{\gamma}} \tag{9}$$

Equation (9) indicates that a consumption drop is decreasing in γ (i.e., households are more reluctant to decrease consumption as γ increases) and increasing in θ_s (i.e., smoothing consumption takes so much effort that it is preferable to tolerate a larger consumption drop.) This expression has an important policy implication: the model predicts that even if the consumption drop is minimal, a safety net is justified on welfare grounds. Based on equation (5), even if $\frac{\Delta c}{c}$ is small, $W \simeq \gamma \frac{\Delta c}{c}$ may be considerably large if poor households are so risk averse that they work extremely hard to maintain consumption stable in the event of a shock (i.e., it is more difficult for a household hit by a weather shock to earn income.) This is a testable prediction that I will take to the data.

5 Data and Measurement

5.1 Household Data: The Progresa Evaluation Surveys (ENCEL)

The household data I employ for the empirical analysis are taken from the communities and households surveys between October 1998 and November 1999 that were carried out to evaluate the impact of the program on several human capital outcomes among poor households in rural areas. Before discussing the data, a description of Progresa is presented.

5.1.1 A brief narrative of Progresa

Progresa, Mexico's National Program of Education, Health and Nutrition, was designed as a policy response to the devastating effects of the Mexican economic collapse of 1994 on disadvantaged regions and the more than sixteen million people that fell into poverty (CONEVAL 2013.)[26] Its main objective was to break the cycle of poverty by

> —[improving] the health and nutritional status of poor households, particularly of their more vulnerable members: children under the age of five and pregnant and nursing women;
> —[contributing] to children's and young people's completion of their primary, secondary, and high school education;
> —[integrating] education, health, and nutrition interventions, so that children's school performance is not affected by ill-health or malnourishment or by the need to work, either inside

[26] For a review of the economic and redistributive policies of Mexico during the 20th century and the politics behind Progresa's conception, implementation, promotion, distribution mechanisms and manipulation safeguards, see De la O Torres (2007), Levy (2009) and Rodríguez Dorantes (2005.) Rodríguez Dorantes (2005) also presents a comprehensive review of the many impact evaluations of Progresa.

> or outside the home;
> —[redistributing] income to families in extreme poverty, increasing their certainty of having a minimum level of consumption;
> —[encouraging] the responsibility and active participation of parents and all members of the family in improving their own and their children's education, health, and nutritional status by giving them sufficient information on these issues and complete freedom with regard to their decisions about family size, children's education, and spending patterns (Levy 2006, p. 21.)

Progresa was a program that targeted the poor through three stages. First, the program was restricted to communities in extreme poverty: a marginality index to measure public service coverage was determined, and only those communities with high and very high marginality indices were selected. Second, the program was limited to poor households: program officials visited all households in participating communities and collected data on observable characteristics indicative of relative wealth, and only those households above a cutoff point were considered eligible. Third, the program verified whether selected households represented the poorest in the area: public meetings to explain the program's rules of operation took place and households who were not originally selected and believed they were in fact eligible for the program were allowed to request a re-evaluation (Levy 2006.)

Progresa was a conditional cash transfer program in nature, with the federal government making monetary transfers conditional upon the recipients' actions. Cash transfers were made once every two months to the female head of the household through bank deposits or at payment centers in each community, as a means to empower women through access to and control over monetary resources. Given that transfers were a function of the number of children in the household, maximum amount limits were set in order to avert higher fertility. Once selected to participate in the program, beneficiary households are entitled to the program's benefits for three years, contingent upon the fulfillment of the program's requirements. After this period, program recipients' needs are re-assessed and may be re-enrolled for an additional three years.

At its inception, Progresa households received a monthly cash stipend indexed to a price index to protect the recipients' purchasing power. Although this cash transfer was intended to improve the nutritional status of the household, families were allowed to use the nutrition subsidy at their discretion. In addition, an in-kind transfer, consisting of a high-nutrient supplement for infants, young children, pregnant and breastfeeding women, was provided. Both of these transfers were conditional on the mandatory healthcare visits to free clinics by all members of the household, which was reported by health providers to program officials. Furthermore, a variable school grant was given during the academic year, provided that recipients attended at least 85% of school days, as certified by school administrators. The grant fluctuated according to the recipient's gender and educational stage, being the subsidy greater for women, given their higher propensity to drop out school, and older children, as the projected income they would have earned in the labor market is higher. Moreover, a school supplies subsidy offered twice a year, along with a high-school completion grant provided at the time of the recipient's graduation (Flores Romero 2010.)[27] Table 1 presents the monthly cash transfer schedule for 1998 and 1999. Overall, between November 1998 and October 1999, the cash transfers received by households averaged 197 pesos of November 1998 per month (roughly 20 US dollars), approximately 20% of the value of monthly consumption expenditures before joining the program (Skoufias 2007.)

Progresa expanded coverage dramatically during its first two years of operation, from 300,000 beneficiary households in 1997 to 2.3 million households in 1999 (see Figure 7.) By the end of 2012, the program covered 5.8 million households, and has long been the largest single poverty alleviation program in Mexico's history (Levy 2006; Ministry of Social Development 2013.)

In order to assess the effectiveness of Progresa, an impact evaluation was carried out, using data from household surveys.[28] I join these data with climatic information at

[27] In 2007, the federal government introduced an unconditional cash transfer to help households cover their electricity bills.

[28] A valuable feature of Progresa is the experimental nature of the data for its evaluation. If both sets of localities and households are chosen randomly and if repeated observations of the same variables are collected for both sets to obtain data before and after program implementation, then econometric techniques can be applied to the resulting databases to obtain numerical estimates of pro-

the community level to study the negative consequences of weather-induced income shocks and the extent to which the program mitigates this effect. Specifically, I use household data for approximately 24,000 households from 506 communities in the states of Guerrero, Hidalgo, Michoacán, Puebla, Querétaro, San Luis Potosí and Veracruz. I take the (panel) data from the October 1998 and November 1999 rounds of the Household Evaluation Survey (ENCEL.) Other rounds were carried out in March 1998 and June 1999, but they are not included in my analysis due to the incomparability of the consumption and income information collected. The survey round of March 2000 could not be employed either, as all households in the control group were already receiving the benefits of the program, those losing the randomization component of the data.

All the variables I use for my empirical analysis are at the household level. Adjust per capita and aggregated individual-level variables using an adult equivalency scale. Following Case and Deaton (2002), I calculate E, the number of equivalent adults in each household, by assigning a value of 1 to every adult household member (A), and a value of 0.3 to each child of 10 years of age or under (K), and by assuming that there are diminishing marginal needs ($\theta < 1$) to each additional (weighted) person: $E = (A + \alpha K)^{\theta}$, where $\theta = 0.9$. In terms of household characteristics, I use data on several head-of-household demographic observables such as gender, age, educational attainment, employment, literacy, indigeneity or ethnic minority self-identification, and land tenure.

Additionally, the November 1999 ENCEL includes data on self-reported risk-mitigation strategies to weather disasters. I include in my dataset categorical variables

gram impacts. That was in fact what happened. Due to budgetary constraints, Progresa began to operate in 320 communities in May 1998, but had not been implemented in other 186 communities by late 1999 (Levy 2006.) In this sense, the phased rollout of the program introduced random assignment. Communities were randomly assigned to the treatment or control groups by the Department of Social Program Evaluation and Monitoring of the Mexican Ministry of Social Development. The first set of communities and families could be considered subject to the effects of Progresa and the second set representative of what happens in the absence of the program (until they are incorporated.) Simply put, the first set would be, using clinical trial terminology, the treatment group, and the second the control group. After randomization, the two groups of households are followed in exactly the same way, and the only differences between them should be those intrinsic to the treatment being compared, i.e., those caused by the program itself.

on the type of weather disaster experienced by the household (drought, flood, hurricanes) and the coping mechanisms they resorted to as a response to these shocks (asset depletion, migration, labor supply adjustments.)

I follow Hoddinott, Skoufias and Washburn's (2000) methodology to generate monetary variables. I separate consumption in a way that is consistent with the theoretical model of consumption smoothing. Food consumption (purchased and self-produced) is the sum of the value of consumption on fruits and vegetables, cereals and grains, meats and animal products, industrial food and the value of food eaten out. In order to value food consumed by a household that was self-produced, I generate community-level food prices and multiply them by the quantity consumed. By taking the median household-level price in the community, I create community-level food specific prices, with the requirement that there be at least 20 prices. If 20 households in the community did not purchase the food, then I look to the municipality, state and national levels. At each level, the median price was used only if there were at least 20 valid prices. Nonfood consumption equals to the sum of the value of consumption on transportation, tobacco, health and personal care, education, household furnishings, energy, clothing, festivals and recreation. The earnings variable is the sum of labor income from the main job and other secondary occupations, informal work activities generating income, remittances, transfers from relatives, friends and the government, pensions, interests and rents received by all members of the household. These variables are expressed in pesos of October 1998 per month per adult equivalent and were deflated using state-level agricultural consumer price indices.

In addition to food consumption in pecuniary terms, physical food consumption is measured in terms of caloric intake per month per adult equivalent. ENCEL includes information regarding the reported amount of food consumed for 36 items. I convert these data into calories by first converting different units of volume into a universal measurement for each product, kilograms in this case. I multiply the kilograms consumed of each of the 36 items by the percentage weight of the food deemed edible (i.e., for a banana this is equal to the weight of the fruit without the peel.) Finally, the edible kilograms of food were converted to calories. My calculations are primarily based on the caloric values estimated by Muñoz et al. (2000) and information provided by the School of Public Health and Nutrition of the Universidad Autónoma de Nuevo León (Mexico) (see Table 2.)

5.2 Meteorological Data

The most essential data to carry out any empirical analysis on weather and its impacts are, of necessity, climatic records. There is a variety of models that provide environmental analysts with climatic observations and some have been employed to assess weather impacts in Mexico in terms of human, environmental, and agricultural outcomes. In studying the impact of severe weather on health and cognitive development, Aguilar and Vicarelli (2011) use precipitation data at 0.5 degree resolution climate grids, which were generated by the Climate Research Unit and the Tyndall Centre for Climate Change Research, both at the University of East Anglia. Sáenz Romero et al. (2010) develop spatial climate models to estimate plant-climate relationships using thin plate smoothing splines of ANUSPLIN software, created by the Australian National University. Pollak and Corbett (1993) use spatial agroclimatic data to determine corn ecologies.

The underlying problem with these and other works that follow similar methodologies is their use of monthly climatic data. Using monthly climatic data is problematic due to the nonlinear effects of weather, which may be concealed when daily observations are averaged into monthly or seasonal variables. In effect, daily and even finer-scale weather data facilitate estimation of models that aim to identify nonlinearities and breakpoints in the effect of weather. Schlenker and Roberts (2009) use daily temperature data and find a nonlinear asymmetric relationship between weather and crops yields in the United States, with yields decreasing more rapidly above the optimal temperature vis-à-vis their increasing below the optimal temperature. The assumption of nonlinearity is particularly critical for studies like this one, where the researcher attempts to represent the relationship between weather and human physiology. In many studies, for the case of mortality, a *J*- or *U*-shaped curve has been found appropriate to describe the association, with elevated mortality being observed at temperature extremes and relatively lower mortality at moderate temperatures (Burgess et al. 2011, Curriero et al. 2002, Deschênes & Greenstone 2011, Huynen et al. 2001, Kunst, Looman & Mackenbach 1993.)

I use daily temperature and precipitation data from the North American Regional Reanalysis (NARR) model (NOAA, 2012.) The NARR project is a long-term, high-frequency, dynamically consistent meteorological and land surface hydrology dataset developed by the National Centers for Environmental Prediction (NCEP) as an extension of the NCEP Global Reanalysis, which is run over the North American Region. It covers the period 1979 to 2010 and data are available at three-hour intervals (i.e., eight data points per day), on a Northern Hemisphere Lambert Conformal Conic grid with a resolution of 0.3 degrees (32km)/45 layers at the lowest latitude. In addition to the modeling benefits of high spatial resolution, I employ NARR due to the model's good representation of extreme weather events, resulting from the model outputting all "native" (Eta) grid time-integrated quantities of water budget. In a recent study, Mesinger et al. (2006) compare the NARR precipitation for January 1998 (when the El Niño effect was underway) with observed precipitation. Their comparison shows that over land there is an extremely high agreement between NARR and observed precipitation, even over the complex western topography of Mexico.

Other variables could be employed for future work. The NARR dataset also includes information on wind speed, humidity, elevation, and other common climatic factors, but evidence shows that, at least for the most important crops of Mexico in terms of output (i.e., corn, sorghum, and wheat), temperature and precipitation are the two weather elements that can effectively inhibit plant growth and development to the point of crop failure (Ministry of Agriculture of Mexico, 2012.) Conversely, non-optimal values in altitude, soil quality, or light intensity requirements may only retard growth or reduce yields, but these factors are not likely to put crops at imminent risk (FAO, 2007.)

I construct daily temperature and precipitation data in two simple steps. First, I apply a spherical interpolation routine to the data: I take weighted averages of the daily mean temperature and accumulated precipitation of every NARR gridpoint within 30 kilometers of each of the 506 Progresa treatment and control villages's geographic center, with the inverse squared haversine distance between the NARR gridpoint and the village centroid as the weighting factor.[29]

Then, I construct four measures of weather that, on the one hand are operative metrics of extreme climate and, on the other hand capture the nonlinear, asymmetric relationship between weather and welfare outcomes. These measures are the cumulative degrees-times-days that exceed 33°C in a year (extreme hot weather), the cumulative degrees-times-days below 5°C in a year (extreme cold weather), the total millimeters-times-days that exceed 30 millimeters (extreme rainfall), and the total millimeters-times-days below 0.5 millimeters (extreme drought.) Even though it collapses daily weather observations into a single metric, these measures, by taking into account the number of degrees/millimeters per day above/below a certain threshold, still indirectly accounts for the nonlinear effects of weather and leads to relative sensitivity gains due to improved statistical power to detect weather effects. These metrics assume that the sequence of relatively hot, cold, rainy and dry days is irrelevant in terms of impact on the annual outcome variable. This assumption is supported by the findings of Burgess et al. (2011.)

Although these cutoff points are arbitrary, the rationale behind these thresholds is ecological. At these values, many crops –including corn, which is an important source of income that also supports self-consumption– undergo severe abiotic stress, greatly increasing the likelihood of crop loss (Gómez Rojas & Esquivel Mota 2002, Ministry of Agriculture of Mexico 2012, Neild & Newman 1990, North Dakota Corn Utilization Council 1997, Wang, Vinocur & Altman 2007) Hence, changes in consumption patterns are expected. Because the functional form of the relationship between weather and welfare is unknown, I also examine other thresholds and specifications to assess the effect of extreme temperatures and precipitation. The results are robust to changes in the thresholds over a reasonable range (data available from the author.) Table 3

[29] The haversine distance measure is useful when the units are located on the surface of the earth and the coordinate variables represent the geographical coordinates of the spatial units and a spherical distance between the spatial units needs to be calculated. This is accomplished by calculating $d_{st} = r \times c$, where r is the mean radius of the Earth (6,371.009 kms); $c = 2\arcsin(\min(1, \sqrt{a}))$; $a = \sin^2\phi + \cos(\phi_1)\cos(\phi_2)\sin^2\lambda$; $\phi = \frac{1}{2}(\phi_2 - \phi_1) = \frac{1}{2}(x_2[t] - x_2[s])$; $\lambda = \frac{1}{2}(\lambda_2 - \lambda_1) = \frac{1}{2}(x_1[t] - x_1[s])$; $x_1[s]$ and $x_1[t]$ are the longitudes of point s and point t, respectively; and $x_2[s]$ and $x_2[t]$ are the latitudes of point s and point t, respectively.

summarizes the descriptive statistics for the temperature and precipitation variables employed.

6 Evaluation Strategy

This section presents the methodology to identify the impacts of several types of extreme weather events on welfare.

The following equation is used to estimate the effect of each type of shock on welfare outcomes:

$$W_{hvt} = \alpha + \beta_1 s_{vt} + X'_{vt}\beta_2 + \gamma_t + \varepsilon_{hvt} \quad (10)$$

where W_{hvt} is the welfare outcome of household h in village v during year t; s_{vt} is the intensity of a given weather shock in village v during year t (i.e., the cumulative degrees-times-days that exceed 33°C in a year); X_{vt} is a vector of time-varying household characteristics; γ_t is a time fixed effect; and ε_{hvt} is the error term.[30]

I operationalize welfare as household consumption per adult equivalent, separately estimating the effect on food and non-food consumption, as well as caloric intake per adult equivalent. I transform these variables to logs for ease of interpretation. Because observing a common variance structure over time is unlikely, I base equation (10) on a cluster-correlated Huber-White covariance matrix estimator, which avoids the assumption of homoskedasticity (Wooldridge 2004.)

Additionally, I am interested in the impact of being a recipient of Progresa on welfare outcomes in the event of a weather shock. I modify equation (10) to account for the effect of being assigned to the treatment group:

$$W_{hvt} = \alpha + \beta_1 s_{vt} + \beta_2 T_{vt} + \beta_3 s_{vt} T_{vt} + X'_{hvt}\beta_4 + \gamma_t + \varepsilon_{hvt} \text{ iff } P_{hvt} = 1 \quad (11)$$

[30] I add a set of conditioning variables, X'_{vt}, to increase the precision of the estimates. The elements of the vector X'_{vt} include household demographic characteristics (household size, percentage of men and women in reproductive age) and characteristics of the head (gender, age, indigeneity, literacy, employment status, and educational attainment.)

where P_{hvt} is a dummy equal to 1 if household h in village v was sufficiently poor during year t to be eligible to join the Program; while T_{vt} is a dummy equal to 1 if village v was randomly selected to join the program during year t. I also adjust standard errors in equation (11) for clustering. Randomized assignment of T_{vt} ensures that $E(\varepsilon_{vt1}|X_{vt}, T_{vt}) = 0$, and therefore OLS estimates of β_2 will be unbiased. To verify randomization, Table 4 presents summary statistics for observable household characteristics in the sample, separately for the control and treatment groups. I also show the difference between the means of the two groups and report the p-value of a test of the null hypothesis that they cannot be distinguished from each other. I adjust the standard errors for clustering. In general, Table 4 corroborates that the random assignment of Progresa generated observably similar treatment and control groups and thus the internal validity of the experiment.[31]

In addition, I obtain estimates of β_2 in equation (11) for specific sample subsets of vulnerable groups, such as households headed by women or elderly persons, indigenous households, and the landless. To allow for such heterogeneity in the treatment effects by household type, I estimate the following equation:

$$W_{hkvt} = \alpha + \beta_1 s_{vt} + \beta_2 T_{vt} + \beta_3 s_{vt} T_{vt} + X'_{hkvt}\beta_4 + \gamma_t + \varepsilon_{hkvt} \text{ iff } P_{hkvt} = 1 \tag{12}$$

where P_{hkvt} is a dummy equal to 1 if household h in village v belonging to the vulnerable group k was sufficiently poor during year t to be eligible to join the program.

Welfare impacts can also be assessed through several qualitative measures. I investigate whether extreme weather shocks increase the probability of a household losing land, harvest, cattle, hardware or their home. I operationalize these welfare shocks as categorical variables. To achieve this, I estimate the following probit model:

$$\text{Prob}(L_{hvt} = 1) = F(\alpha + \beta_1 s_{vt} + X'_{vt}\beta_2) \text{ iff } P_{hvt} = 1 \tag{13}$$

[31] Of course, even if random assignment was well executed, it is possible that experimental groups will not be statistically equivalent on all possible dimensions or on any one characteristic (Mutz & Pemantle 2011.)

where F is the cumulative normal distribution and L_{hvt} if a dummy variable equal to 1 if household h in village v reports a loss resulting from an extreme weather event during year t.

Finally, in a similar exercise, I determine the extent to which households resort to costly self-insurance strategies in the event of a weather-induced shock, as well as whether program recipiency changes the behavior of households. I am interested in the impact of extreme-weather shocks on the probability of households undertaking several risk-coping strategies, specifically asset depletion, forced migration, or labor supply adjustments. I operationalize these responses as categorical variables. To achieve this, I estimate the following probit model:

$$\text{Prob}(R_{hvt} = 1) = F(\alpha + \beta_1 s_{vt} + \beta_2 T_{vt} + \beta_3 s_{vt} T_{vt} + X'_{vt}\beta_4) \text{ iff } P_{hvt} = 1 \qquad (14)$$

where F is the cumulative normal distribution and R_{hvt} if a dummy equal to 1 if household h in village v resorts to any given *ex post* risk-coping strategy during year t.

Similarly, an alternative mitigation strategy to decreasing consumption is for households to spend their food budget differently. If an unexpected shock decreases household income, households may resort to changing their diet and consuming "cheaper" calories provided by inferior goods, i.e., cereals instead of meat, or coarse cereals instead of wheat (Jensen & Miller 2008.) Even though food expenses may decrease as a result of a weather shock, caloric intake may remain relatively stable.

To test whether this phenomenon is observed in my sample, I estimate the relationship between calories consumed, the quality of food, and the resources available for food consumption by calculating the elasticity of per adult equivalent caloric intake to per adult equivalent food consumption, as well as the elasticity of food quality (calorie price) with respect to per adult equivalent food consumption.

Theoretically, the relationship between food consumption and calorie intake and price is unlikely to be homogeneous for every level of income. In a well-known paper, Strauss and Thomas (1990) find that when a certain calorie threshold is reached, households switch to higher protein foods while maintaining an approximately constant level of calorie intake. Consequently, the use of a linear form in a parametric analysis would be inappropriate. I follow Subramanian and Deaton's (1996) non-parametric approach to estimate a regression function of caloric intake (as well as food quality) on food consumption. As my objective is to estimate elasticities, I use log values throughout this exercise.

Consider the non-parametric regression function $m(x) = E(y|x)$, where y is the per adult equivalent caloric intake and x is the per adult equivalent food consumption. Drawing from Subramanian and Deaton (1996), I estimate *m(x)* using a smooth local regression technique for both the Progresa treatment and control groups. I employ an evenly spaced grid of 50 points of x over the range [3,6] and run for each point a weighted linear regression, with each observation getting a quadratic kernel weight equal to

$$w_i(x) = \begin{cases} \frac{15}{16}\left[1 - \left(\frac{x - x_i}{h}\right)^2\right]^2 \forall - h \leq x - x_i \leq h \\ \quad 0, \ \text{otherwise} \end{cases} \tag{15}$$

I set the bandwidth $h = 0.5$. The estimate of $m(x)$ comes from the 50 predicted values from the local regression at x, while $m'(x)$, the local estimated slope coefficient $\hat{\beta}(x)$, is used as an estimate of the elasticity. I obtain standard errors for the regression function and its slope by bootstrapping with and without allowance for cluster design.

To complement the analysis, I also carry out a typical regression analysis. I specify the following model of caloric availability and quality:

$$cal_{hvt} = \alpha + \beta f_{hvt} + \gamma_t + \epsilon_{hvt} \tag{16}$$

where cal_{hvt} denotes a caloric outcome of interest (i.e., availability or quality), and f_{hvt} is the log per adult equivalent food consumption. In addition, I specify equation (16) as an OLS regression allowing for slope shifts over time, with and without the inclusion of a vector of time-varying household characteristics. To allow caloric outcomes to vary non-linearly with food consumption, I also include the term βf_{hvt}^{-1}, so that the household's elasticity is given by $\beta_1 f_{hvt} - \beta_2 f_{hvt}^{-1}$ (Graham & Powell 2008.)

7 Results

7.1 The Impact of Weather Shocks

Extreme weather has a negative impact on the welfare of rural households, given that adverse climatic events impact agricultural productivity and crop yields, thus reducing, often drastically, household income. Table 5 presents the impact of weather extremes on consumption based on equation (10.) It compares whether climate has a more acute impact on the poor vis-à-vis the non-poor. I consider a household to be non-poor if its income falls within the top decile of the non-eligible household income distribution.

Regardless of the model specification, the results show that in the event of a weather shock, the poor are disproportionately affected. For instance, a 1-degree increase in the cumulative number of degrees-times-days that exceed 33°C (abnormal heat metric) in a year decreases consumption in 1.7-2.2% among the poor, compared to 0.8-1.4% among the non-poor. Likewise, a 1-degree increase in the cumulative degrees-times-days below 5°C (abnormal cold metric) in a given year decreases consumption among the poor by 0.7-1.9%, while consumption among the non-poor is only reduced by 0.1-0.3%.

Similar results are found for precipitation extremes. A 1-centimeter (ten-millimeter) increase in the number of total millimeters-times-days that exceed 30 millimeters (abnormal rainfall metric) leads to a 0.5-0.7% consumption fall among the poor, compared to a 0.4% consumption decrease among the non-poor. Finally, a 1 centimeter increase in the yearly millimeters-times-days below 0.5 millimeters (extreme drought metric) is associated with a 0.2-0.5% decrease in consumption among the poor, while consumption among the non-poor is only reduced up to 0.3%. While the consumption drop point estimates are highly significant for the poor, they are statistically equal to zero in several instances among the non-poor. In effect, the Wald statistic (for testing equality of impacts between the poor and the non-poor) is in all but one case statistically significant at the conventional levels, suggesting that the impact of weather shocks do in fact differ between these two groups.

An important distinction is that households do not make consumption reduction decisions homogeneously. In a poverty situation, an unanticipated income shock is expected to cause acute drops in non-food consumption, while comparatively maintaining food consumption stable. If households are at, or near, subsistence levels, they will opt to give up consumption of relatively unnecessary goods first, as they cannot make cuts to food consumption without forcing family members below a minimum calorie intake for survival.

Table 6 reports the results from estimating equation (10), separately for food and non-food consumption. As expected, in the face of an unexpected weather-induced income shock, poor households will try to maintain their already low food consumption levels by initially cutting non-food consumption. Non-food consumption drops are at least twice and up to four times as large as food consumption drops: extreme temperature coefficients are associated to a 1.5-1.6% decrease in food consumption, and a 3.0-4.5% decrease in non-food consumption. Similarly, extreme precipitation coefficients are associated to a 0.03-0.04% reduction in food consumption, and a 1.1-1.5% reduction in non-food consumption. For the four types of extreme weather events considered in this paper, the hypothesis of equality of impacts between food and non-food consumption is rejected at the conventional confidence levels.

7.2 The Impact of Safety Nets

The analysis has provided evidence on the negative impact of weather-induced income shocks. Table 8 shows that the contraction in both food and non-food consumption is effectively mitigated by program affiliation. In the absence of shocks, the *raw* treatment effect is significant: depending on the model specification, Progresa increases food consumption by 11-29% as well as non-food consumption by 6-52%. More importantly, Progresa also proves to be effective as a consumption smoothing mechanism *in the event* of a weather shock.

Consider the impact of weather extremes on food consumption (Column 1): for program non-beneficiaries, the effect of an additional degree-day above (below) the abnormal heat (cold) threshold leads to a statistically significant 1% (2%) drop in food consumption. Conversely, the program shielded its recipients by insulating them from the weather shock: the *differential* effect of the program reflects that in spite of an extreme temperature event hitting the household, food consumption changes are statistically undetectable. A similar result is found for extreme precipitation shocks. The effect of an additional centimeter above (below) the abnormal rainfall (drought) threshold leads to a very precisely estimated 4% drop in food consumption among non-beneficiary households, while beneficiary households affected by a precipitation shock maintained their food consumption stable.

Non-food consumption regressions (Column 3) lead to comparable results, although with higher-order magnitudes. For program non-beneficiaries, the effect of an additional degree-day above (below) the abnormal heat (cold) threshold leads to a statistically significant 4% (5%) drop in non-food consumption. Conversely, the program shielded its recipients by insulating them from the weather shock: the *differential* effect of the program reflects that in spite of an extreme temperature event hitting the household, non-food consumption changes are, at worst, statistically undetectable or even positive. Likewise, the effect of an additional centimeter above (below) the abnormal rainfall (drought) threshold leads to a tightly estimated 13% (16%) drop in non-food consumption among non-beneficiary households, while beneficiary households affected by a precipitation shock exhibit no statistically significant changes in their non-food consumption. Expectedly, regardless of the extreme weather model specification, the hypothesis of equality of impacts between food and non-food consumption is rejected at the conventional confidence levels.

7.3 Heterogeneity in the Treatment Effect

In this section, I discuss the results of the analysis where I investigate whether extreme weather impacts and treatment effects vary with specific characteristics of the head of the households. Table 10 presents estimates of the impact of extreme weather on several segments of the population typically deemed vulnerable in the literature, such as households headed by women or elderly persons, as well as indigenous and landless households, among others.

Overall, I find little heterogeneity for the precipitation model specifications: the hypothesis of equality of abnormal drought coefficients is not rejected at the conventional levels, while the abnormal rainfall coefficients are statistically different from each other only at a 90% confidence level. Nevertheless, when the temperature shock regressions are considered, I find significantly larger extreme weather impacts for indigenous households (Columns 7 and 8) and relatively acuter impacts for female-headed households (Columns 3 and 4): depending on the specification, extreme temperature shocks lead to a decrease in consumption in female-headed households between 4 and 50% larger than that of the typical household. Similarly, they cause a drop in consumption in indigenous households between 60 and 250% larger than that of the typical household. However, the negative impacts of extreme weather are, in general, completely smoothed by the treatment, even for those seemingly vulnerable groups.

7.4 Weather's "Sibling Rivalry"

El Niño- and La Niña-related meteorological conditions were responsible for extreme weather conditions in Mexico (Magaña et al. 2004.) The World Meteorological Organization's World Climate Services Programme (WMO 2012) reports that "research conducted over recent decades has shed considerable light on the important role played by interactions between the atmosphere and ocean in the tropical belt of the Pacific Ocean in altering global weather and climate patterns. During El Niño events, for example, sea temperatures at the surface in the central and eastern tropical Pacific Ocean become substantially warmer than normal, while shifting eastward intense tropical rainfall in the region. In contrast, during La Niña events, the sea surface temperatures in these regions become colder than normal, while shifting westward intense tropical rainfall in the region. These temperature changes are strongly linked to major climate fluctuations around the globe and, once initiated, such events can last for 12 months or more."

Because of the timing of El Niño of 1998 and La Niña of 1999, the impact of these weather events is likely to be captured by the Progresa evaluation data, derived from surveys carried out in October 1998 and November 1999. The strong El Niño event of 1997-1998 was followed by a prolonged La Niña phase that extended from mid-1998 to early 2001. But do these opposite phenomena cause major redistributions of extreme weather events, thus having differentiated impacts on welfare? This is an important distinction in terms of household adaptation policy design and natural disaster assistance programs in the agricultural sector.

Table 11 shows that the impact of these events is similar. The extreme weather point estimates suggest that El Niño intensified the impact of abnormal cold and drought on household consumption. This goes in line with Magaña et al. (2004), who find that El Niño events lead to colder, drier winters in central Mexico. Conversely, it appears that La Niña increased the effect of abnormal heat and rainfall on household consumption. Indeed, Magaña, Pérez and Conde (2008) argue that anomalous extreme rainfall patterns are to be expected as a result of a La Niña event. Nonetheless, the Wald test indicates that, regardless of the extreme weather model specification, the difference between El Niño and La Niña impact is not significant from a statistical standpoint, with p-values ranging from 19 to 91%.

7.5 Other Welfare Impacts

The impact of extreme weather is multidimensional and goes beyond its effect on household consumption. Household vulnerability may also be reflected in the extent to which exposure to severe climate causes material losses. A material loss can be interpreted as the result of the households' inability to mitigate the impact of the shock. The Progresa evaluation data include a variety of measures of self-reported losses. Shock impacts include loss of arable land, harvest, home, tools and hardware and animals, as well as the death of a member of the household as a result of a natural disaster.

Table 12 presents estimates of the impact of abnormal temperature and precipitation patterns on these six shock impacts. Overall, I find no effect of extreme weather on death of household members and loss of tools and household hardware. Similarly, the home loss coefficients change sign from one model specification to the next, suggesting no consistent pattern. Surprisingly, I find that, with the exception of abnormally cold weather, severe climate in general does not lead to cattle death loss. Eakin (2006) attributes this to the fact that most households living in poverty do not own any animals in the first place. Using survey data collected for a study of agricultural vulnerability and adaptation in Tlaxcala, Mexico, she finds that only 36% of households owned a yoke, and half of the survey respondents did not have any pigs, goats or sheep.

As expected, extreme weather shocks have a direct effect on the loss of arable land as well as harvest loss. The point estimate for the average effect across all extreme weather model specifications is a 0.2% increase in the probability of a household losing arable land. The addition of various control variables does not change the results. The impact of extreme weather on harvest loss is more acute, particularly for the extreme temperature regressions. These coefficients are precisely estimated (z scores in the 5 to 9 range) and quantitatively important. I find that being hit by an extreme temperature shock increases on average the probability that a household loses their harvest by 2.2%. Similarly, the abnormal precipitation models show that being hit by an extreme rainfall or drought shock increases on average the probability that a household loses their harvest by 0.4%.

7.6 Risk-Coping Strategies

Poor households are more likely to resort to a reduction in consumption rather than other strategies to cope with a variety of shocks (World Bank 2003.) However, the severity of the shock may trigger a variety of household *ex post* risk-coping mechanisms, including borrowing money, selling assets, diversifying crop production, augmenting the labor of those already working or of other members of the family (including children), seeking job elsewhere, or receiving family aid to cope with the effects of shocks. As I discuss in the next section, households may also switch to cheaper diets, sacrificing calorie quality and taste. Regardless of the risk-coping strategy, however, it is clear that all of them are likely to decrease the welfare of the household by rendering its members more vulnerable and shifting them to even lower standards of living in the medium and long terms.

Because of the additional income the cash transfer provides, families may be prevented from employing these costly strategies in the event of a weather shock. Hence, the estimated marginal effect of treatment should be a reduction in the probability of adopting a specific risk-coping response. Yet, as the intensity of the shock increases, the treatment effect may diminish.

The results of probit estimations are presented in Figures 8-16. Overall, average marginal treatment effects are imprecisely estimated. Although in most cases, regardless of the type of weather shock, the point estimates suggest that Progresa does decrease households' propensity to resort to a risk-coping strategy in the event of a severe climate shock, the coefficients are never statistically different from zero. One can only assess with low confidence that the program reduces the probability of the household sending children to work by 2-3% (Figure 8.) Conversely Progresa may fail to prevent animal asset depletion, and slightly increase the probability of crop diversification, probably as a result of the program enabling farmers to afford other crop varieties (Figures 9 and 10.) For low-intensity weather shocks, the program seems to reduce the probability of households augmenting their labor supply, but this effect disappears as weather shocks become more intense (Figure 11.) In terms of the effect of the program on the probability of households getting family aid, none of the coefficients are significant, and their sign changes from one weather shock to the next, suggesting no consistent pattern (Figure 12.)

The program has virtually no effect on forced domestic migration decisions (Figures 13-15), but the (imprecisely estimated) coefficients suggest that, in the event of a weather shock, Progresa beneficiaries may have a higher propensity to migrate abroad, particularly to the United States: depending on the model specification, the treatment group has a 1-5% higher likelihood than the control group of moving as a result of economic struggles and hardship (Figure 16.) Angelucci (2004, 2012), who previously evidenced this migration dichotomy, argues that this finding is consistent with economic theories predicting that, by relaxing credit constraints, a cash transfer increases international migration, which is more costly than domestic migration. The implication is that financial constraints to international migration are binding for poor Mexicans, some of whom would like to migrate but cannot afford to.

The fact that there does not appear to be any significant differences in how Progresa beneficiaries and non-beneficiaries respond to these shocks was first approached by Skoufias (2007), who studied the impact of income shocks (rather than weather shocks) on household behavior in terms of self-insurance strategies. While it is possible that the impact of the program is negligible, the possibility that the Progresa data suffer from under-reporting biases cannot be ruled out. The literature on the accuracy of self-reporting risk coping mechanisms suggests that the likelihood of reporting specific strategies is associated with the poverty status of the household, the intensity of the strategy, the legality of the strategy, or the need for justification thereof (Christiaensen, Hoffmann & Sarris 2007; Kidolezi et al. 2005; Mahmoud & Trebesch 2010; Meyer, Mok and Sullivan 2009.)

7.7 Resilience through Caloric Intake Recomposition

The evidence so far has shown that, when confronted with unexpected weather shocks, food consumption decreases. Even though the decline in food consumption is of smaller magnitude when compared to changes in non-food consumption, it is still statistically significant. If, as theorized, households hit by a weather shock resort to changing their diet and consuming "cheaper" calories provided by inferior goods, one would expect to see at best households maintaining their caloric intake in spite of a drop in food consumption. At worst, switching to cheaper calories may imply a loss of micronutrients in the household's diet. Table 7 reports that, regardless of the type of shock considered, it appears that the nutritional status of the household is resilient to weather-induced variation in household resources. Compared to the impact of weather on total consumption, caloric intake remains reasonably unaffected, generally as stable as food consumption. In some instances, caloric intake estimates are statistically equal to zero. Although for the abnormal cold regressions the decline in caloric intake is larger than the decline in food consumption, usually changes in food consumption are significantly larger in magnitude. For instance, a 1-degree increase in the cumulative number of degrees-times-days that exceed 33°C in a year decreases food consumption by 1.5%, while virtually having a zero-effect on caloric intake. Similar outcomes are found for the extremes in the precipitation distribution regressions. The Wald test of equality is rejected in two cases, and for the other two cases, there is suggestive evidence that food consumption decreases more considerably than caloric intake.

Reassuringly, the results are analogous when accounting for the impact of Progresa. Table 9 shows that, with the exception of the abnormal drought regression, the treatment effect in terms of food consumption is of larger magnitude than the effect with respect to caloric intake. In other words, the impact of a cash transfer on food expenses is larger than that on nutrient consumption. Consider the abnormal heat regression: program affiliation increases food consumption by 13%, while caloric intake increases by only 10%. Similarly, the abnormal cold regression shows that while a cash transfer increases food consumption by 11-12%, caloric intake increases by 9-10%. In terms on the rainfall regression, program affiliation leads to a 13% increase in food consumption, while increasing caloric intake by only 8%. This *a priori* suggests that increases in income are not directly translated into improvements in nutritional status but, rather, that households are now able to buy better quality food that is less nutritious per dollar spent. This is in fact what the data show.

Figure 17 presents the local regression estimate for log per adult equivalent caloric intake and log per adult equivalent food consumption, for both treatment and control groups. The inner broken lines are two standard error bands with no allowance for cluster design, while the outer bands show the clustered bootstrap. The regression estimate is tightly estimated and shows an almost linear relationship between caloric intake and food consumption, with the treatment group showing a slightly higher caloric intake than the control group. The slope of this graph is approximately 0.34: when the monetary value of food consumption per adult equivalent increases by 10%, the per adult equivalent calorie consumption increases by 3.4%. The control group exhibits a similar behavior, with per adult equivalent calorie consumption increases by 3.2% given a 10% increase in the amount spent on food consumption.

Similarly, Figure 18 illustrates the local regression estimate for log of price per calorie and log per adult equivalent food consumption, again for both treatment and control groups. Visually, the functional form that best describes this relationship is again linear, although the slope is flatter: when the monetary value of food consumption per adult equivalent increases by 10%, the price per calorie roughly increases by 2% for both treatment and control groups. This shows that when households spend more money on food, they buy more expensive calories. Conversely, when households are hit by a shock that decreases their food expenses, they try to stabilize their caloric intake by consuming "cheaper" calories.

Figure 19 shows the estimated elasticities of calorie intake and calorie price for program recipients, with more conservative clustered and unclustered bootstrap standard errors. Both elasticities are always below 0.6. At the median log of per adult equivalent food consumption, the elasticity of calorie intake is roughly 0.4, while the elasticity of calorie price is approximately 0.3. This range reflects that poor households' demand for calories increases with income, if not proportionately, given that they substitute quality for quantity, certainly with an elasticity greater than zero (Subramanian & Deaton 1996.) This finding is in accord with the elasticities Skoufias et al. (2011) estimate for a sample of poor households from rural Mexico affiliated to a targeted nutritional program.[32]

While non-parametric regressions are useful to explore bivariate relationships, they are ineffective to account for multiple variables that simultaneously have an indirect effect on the relationship (Subramanian & Deaton 1996.) Table 13 presents elasticity estimates from three sets of parametric regressions based on equation (16.) Panel A displays the results from a typical ordinary least squares estimation. It consistently shows that the calorie intake elasticity is higher than the calorie price elasticity (roughly 0.6 and 0.4 respectively.) Estimates for treatment and control groups are similar as expected. Similarly, Panel B reports a model specification allowing elasticities to vary non-linearly with food consumption, containing common intercept and slope time shifts. Average elasticities are analogous to their linear counterparts. Finally, Panel C modifies the model to include intercept shifts only. This specification does not change elasticity coefficients significantly. In the three panels, the total expenditure elasticity of expenses on food consumption is close to one, with a near 60/40% split between the elasticity of calorie intake and calorie price. A poor household that is 10% richer spends about 6% more on food and 4% on more expensive (better quality) calories. In

[32] For a summary of the literature on the response of nutrient intake to income changes or other income proxies, see Ogundari and Abdulai (2012.)

terms of this paper, the main implication of this evidence, which is in accord with the findings of Stillman and Thomas (2007), is that households are able to cope with unexpected fluctuations in income by switching to cheaper diets, sacrificing calorie quality, taste and potentially micronutrients. Put in another way, even among very poor people, the impact of a cash transfer program on the nutritional status of the household is certainly positive, but rather limited.

7.8 Progresa's Overall Impact on Welfare

The basic model of social insurance for the poor presented at the beginning of this paper predicts that even if Progresa increases consumption among poor households, its impact has broader welfare implications, particularly when poor households are so risk averse that they work extremely hard to maintain consumption stable in the event of a shock. As shown above, not only does extreme weather decreases consumption, but also increases the likelihood of arable land and harvest loss. Similarly, poor households switch to cheaper diets, sacrificing calorie quality, taste and potentially micronutrient content. Although not conclusively, evidence suggests that as a result of a weather shock, families resort to very costly *ex post* risk-coping strategies. *Prima facie*, scarcity of resources derived from weather shocks fosters risk aversion and impatience in the short run (Duflo 2006.) Conversely, a program like Progresa reduces reliance on costly consumption-smoothing mechanisms when households are hit by shocks.

Although there is substantial debate in the economics and finance literature with respect to the value of the coefficient of relative risk aversion (γ), some authors have directly or indirectly carried out its empirical parametrization for Mexico. Reinhart, Ogaki & Ostry (1996) estimate the lower and upper bounds of the intertemporal elasticity of substitution (i.e., $\frac{1}{\gamma}$.) Based on their analysis, γ for Mexico lies in the 1.2-2.3 range. In a previous study using data for Mexico, Brazil, Colombia, and Costa Rica, Ostry & Reinhart (1992) show that γ for these four countries ranges between 2.3 and 2.7. In another regional exercise, Rossi (1988) finds that γ for Mexico and Central American countries is 2.7.

Considering that these calibrations are nationwide, it is plausible that the poor-specific risk-aversion coefficients are higher. Using the survey data for the Progresa evaluation, however, Pavan & Colussi (2008) find that the coefficient of risk aversion for borrowing-constrained, poor households equals to 2.25. Likewise, for another study using the Progresa data, Cho (2005) assumes that $\gamma = 2.0$.

Based on these values of the coefficient of relative risk aversion and the estimated consumption gains derived from being a recipient of Progresa (presented in Table 8), Table 14 presents several simulations of the implied welfare gain set for a range of γ. Notice that the marginal gain in welfare from the provision of Progresa can be almost three times as large as the increase in total consumption, depending on the household's level of risk aversion: even though Progresa may help households increase consumption by 11-34% in the event of an extreme weather shock, there are substantial welfare benefits for beneficiary households, whose expected utility increases between 32 and 93%. In sum, I find that the provision of a safety net raises welfare by reducing *ex post* inefficient behaviors.

8 Conclusion

Extreme weather is a major source of vulnerability for rural poor households. Not only does it decrease their welfare in the short term, but it also makes it harder for families to get out of poverty in the medium and long terms, given the suboptimal risk-coping responses constrained agents resort to as well as their inability to replenish assets. If the frequency and severity of extreme weather events is likely to increase as a result of climate change (Skoufias 2003), household inefficient decisions are likely to become more recurrent, leading to sharp increases in poverty and inequality as a result.

By combining experimental data for 24,000 households in 506 communities of rural Mexico for 1998 and 1999 with extreme-weather metrics that account for the non-linearity of climate impacts, I show that El Niño- and La Niña-related severe meteorological conditions lead to sharp declines in consumption and disproportionately affect the poor. Extreme temperature, as described herein, decreases consumption by 0.7-2.2% among the poor, compared to 0.1-1.4% among the non-poor. Likewise, precipitation extremes lead to a 0.5-0.7% consumption fall among the poor, compared to a 0.3-0.4% consumption decrease among the non-poor. These differences are significant and robust to several model specifications. As expected, I find that non-food consumption drops are at least twice and up to four times as large as food consumption drops. Moreover, my analysis indicates that female-headed and indigenous households are particularly vulnerable to weather shocks: for these two groups in particular, the contraction in consumption resulting from extreme weather is considerably (up to 250%) larger than that of the typical poor household.

I present evidence that climate-induced changes in welfare are multidimensional and not limited to their impact on consumption. In particular, extreme weather shocks increase the probability of a household losing arable land and their harvests. Although the change in probability is modest, it is precisely estimated.

I also examine the role of Progresa, an anti-poverty program providing conditional cash transfers to its beneficiaries, in mitigating vulnerability among poor households. I exploit the fact that the phased rollout of the program introduced random assignment to evaluate its impact on welfare. I find the program effectively increases both food and non-food consumption in situations where no weather shocks are observed. More importantly, I show that the program also shields its recipients by insulating them from weather-induced income shocks: program recipients smoothed consumption in a way that food consumption changes are often statistically undetectable.

In addition, I provide suggestive evidence that, as a result of the program, households are less likely to resort to costly *ex post* risk-coping strategies when affected by an extreme weather shock. I find that the program reduces the probability of the household sending children to work by 2-3%, while diminishing the propensity of adult members working more by 1%. I report that the program increases the probability of crop diversification by 1% according to most model specifications. In addition, my estimates show that program beneficiaries are 1-5% more likely than non-beneficiaries to seek job opportunities in the United States. These results, however, should be interpreted with caution, because none of the individual coefficients are significant. Finally, I provide evidence that a risk-coping strategy is for both treatment and control households to switch to cheaper diets to compensate for the loss of income derived from a weather shock: a poor household that is 10% poorer, roughly spends about 6% less on food and 4% on less expensive (lower quality) calories. Overall, the combination of mitigated consumption drops and reduced suboptimal *ex post* behavior by Progresa lead to important welfare gains. Considering risk aversion patterns akin to poor rural households, the expected utility for beneficiary households increases twice as much as consumption.

In conclusion, a targeted program that transfers income in cash and explicitly includes disciplinary components in its *modus operandi* can make an important contribution to vulnerability mitigation, even in cases where the transfer is fungible. Both at the micro (Duflo, Hanna & Ryan 2012) and macro level (Amsden 2009), there is theoretical recognition and empirical support for the tactical efficacy of control mechanisms, which implicitly suggests that there is a positive role for the state at the center of development planning (Amsden 2001.)

In devising poverty policy, more attention should focus on understanding the economic and institutional factors that influence risk and how crisis management programs influence the behavior of the household, especially in the context of extreme vulnerability. Whether vulnerability mitigation in the short term leads to poverty alleviation in the long term is still an open question that should be analyzed in subsequent work. While I studied the effect of a state intervention on *ex post* risk-coping mitigation strategies, future research should also focus on the evaluation of government actions that enhance *ex ante* risk-mitigation mechanisms, such as rural technological change (Amsden 2010) and infrastructure development (Polenske & Rockler 1993.)

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Table 1. Program Monthly Cash Transfer Schedule (in U.S. Dollars of November 1998), 1998-1999

Subsidy component	1998	1999
Nutrition grant per household[a]	9.3	13.3
School grant per child[b]		
Primary		
3rd grade	6.4	8.6
4th grade	7.4	10.3
5th grade	9.3	13.3
6th grade	12.6	17.5
Secondary		
1st grade (male)	18.5	25.5
1st grade (female)	19.5	26.9
2nd grade (male)	19.5	26.9
2nd grade (female)	21.6	29.9
3rd grade (male)	20.4	28.3
3rd grade (female)	23.5	32.7
School supplies subsidy		
Primary	1.9	8.6
Secondary	8.1	11.4
Maximum grant per household	57.5	80.1

Note: (a) conditional on school enrollment and attendance for at least 85% of school days; (b) conditional on healthcare visits to clinics.
Source: Levy, S., personal communication, April 11, 2013.

Table 2. Caloric Values for Foods and Products Included in the Household Evaluation Survey

Food	Caloric Content		Edible content (%)
	Per kg.	Per unit	
Fruits and vegetables			
Tomatoes	190	24	88
Onions	400	44	86
Potatoes	760	162	82
Carrots	440	27	82
Green leafy vegetables	190	119	69
Oranges	470	62	63
Bananas	860	101	68
Apples	650	118	69
Lemons	620	36	20
Cactus leaves	270	23	78
Cereals and grains			
Tortillas	2,140	51	100
Corn	3,500	2,800	92
White bread	2,920	82	100
Pastries	3,840	246	100
Sliced bread	2,850	1,425	100
Wheat flour	3,770	3,770	100
Dry packaged soup	3,400	680	100
Rice	3,640	3,276	100
Crackers	4,230	783	100
Beans	3,320	2,988	100
Breakfast cereals	3,890	1,323	100
Meats and animal products			
Poultry meat	930	339	100
Beef and pork	2,750	154	60
Sheepmeat and goatmeat	1,360	76	58
Fish and seafood	920	150	50
Canned tuna and sardine	2,820	479	100
Eggs	1,580	52	88
Milk	610	610	100
Cheese	1,460	730	100
Lard	9,020	2,255	95

Table 2., continued.

Food	Caloric Content		Edible content (%)
	Per kg.	Per unit	
Industrial food			
Snack cakes	3,980	207	100
Carbonated soft drinks	440	156	100
Alcoholic beverages	460	150	100
Coffee	1,180	118	100
Sugar	3,840	3,840	100
Vegetable oil	8,840	8,840	100

Source: Muñoz (2002), School of Public Health and Nutrition, Universidad Autónoma de Nuevo León.

Table 3. Weather Descriptive Statistics

		Mean (1)	Minimum (2)	Maximum (3)
	Temperature			
	Annual mean (°C)	18.7	10.2	26.2
		(4.1)		
	Cumulative-degree days			
Abnormally hot	Above 30°C	11.9	0.0	129.2
		(27.0)		
	Above 33°C	1.0	0.0	19.5
		(2.7)		
	Above 35°C	0.0	0.0	1.2
		(0.1)		
Abnormally cold	Below 10°C	27.7	0.0	326.7
		(45.7)		
	Below 7°C	5.0	0.0	57.0
		(8.0)		
	Below 5°C	1.6	0.0	13.9
		(2.8)		

		Mean (1)	Minimum (2)	Maximum (3)
	Rainfall			
	Annual mean (cm)	2.2	0.5	3.9
		(0.8)		
	Cumulative-centimeter days			
Abnormally rainy	Above 1	15.4	0.0	35.1
		(10.4)		
	Above 2	3.5	0.0	12.0
		(3.1)		
	Above 3	0.9	0.0	4.5
		(1.2)		
Abnormally dry	Below 0.1	21.5	15.6	29.1
		(2.7)		
	Below 0.05	10.0	6.9	13.8
		(1.4)		
	Below 0.01	1.8	1.1	2.6
		(2.8)		

Table 3., continued

		Mean (1)	Minimum (2)	Maximum (3)
	*Annual extreme days**			
Extreme heat	Above 90th percentile	46.1	9	82
		(20.9)		
	Above 95th percentile	28.4	2	60
		(18.8)		
	Above 99th percentile	9.0	0	26
		(9.0)		
Extreme cold	Below 10th percentile	30.5	14	69
		(8.6)		
	Below 5th percentile	16.0	7	44
		(4.8)		
	Below 1st percentile	3.8	0	11
		(1.6)		

		Mean (1)	Minimum (2)	Maximum (3)
	*Annual extreme days**			
Extreme rainfall	Above 90th percentile	28.2	4	51
		(9.7)		
	Above 95th percentile	11.9	0	31
		(6.7)		
	Above 99th percentile	1.8	0	9
		(1.7)		
Extreme drought	Below the median[1]	176.5	0	223
		(47.1)		
	Below 45th percentile[1]	130.1	0	207
		(74.6)		
	Below 35th percentile[1]	46.5	0	171
		(66.5)		

Notes: *The number of extreme temperature (rainfall) days is defined as annual count of days when the daily temperature (precipitation) is above or below the n-th percentile for the base period 1979-2010. Abnormally cold patterns are summations of negative differences between the mean daily temperature and the temperature base (threshold.) To avoid possible confusion, this table presents absolute magnitudes. The same logic applies to the abnormally dry patterns. (1)Given that rainfall patterns are best described by a gamma distribution, which is right-skewed and bounded at zero, a good approximation to "extreme drought" is the number of single-day rainfall events below the 35th-50th percentile. For years 1998 and 1999, there are no observations below the first quartile for the base period.

Table 4. Orthogonality of Treatment to Household Characteristics

Variable	P>|t|	
Head characteristics		
Elegible for Progresa	0.596	
Female	0.684	
Senior (65+ years)	0.908	
Indigenous	0.873	
Literate	0.899	
Employed	0.358	
Farmer	0.900	
Has access to healthcare	0.434	
Education		
No education	0.903	
Primary school	0.766	
Secondary school	0.984	
High school	0.313	
University	0.284	
Household characteristics		
Size (adult equivalent)	0.191	
Accumulated years of schooling	0.802	
Men in reproductive age (%)	0.790	
Women in reproductive age (%)	0.120	
Landless household	0.369	
Hectares of land used last year	0.815	
Health		
At least one adult was sick last week	0.439	
At least one child was sick last week	0.227	
At least one child had diarrhea last week	0.749	
At least one child had fever last week	0.273	
At least one child had the flu last week	0.671	
At least one child had a respiratory disease last week	0.571	
Accumulated sick days last month	0.211	
Log of income per adult equivalent	0.431	
Log of food consumption per adult equivalent	0.000	***
Log of non-food consumption per adult equivalent	0.177	
Log of caloric intake per adult equivalent	0.000	***
Shocks experienced		
Drought	0.569	
Flood	0.465	
Frost	0.693	
Fire	0.516	

Table 4., continued

Variable	P>|t|
Head characteristics	
Shocks experienced	
Plague	0.341
Earthquake	0.692
Hurricane	0.707
Vulnerability	
Lost land	0.139
Lost harvest	0.525
Lost home	0.227
Lost tools	0.230
Lost cattle	0.266
A household member was hurt	0.538
A household member died	0.679
Risk-coping strategies	
Sold cattle	0.685
Borrowed money	0.510
Worked more	0.258
Received help from family	0.715
Received help from the government	0.135
Sent children to work	0.121
Migrated	0.609
Within the same municipality	0.815
To another municipality within the same state	0.172
To another state	0.843
To the United States	0.827
Weather variables	
Cumulative degree-days above 30°C	0.329
Cumulative degree-days above 33°C	0.310
Cumulative degree-days above 35°C	0.125
Cumulative degree-days below 10°C	0.929
Cumulative degree-days below 7°C	0.995
Cumulative degree-days below 5°C	0.726
Cumulative millimeter-days above 10mm	0.199
Cumulative millimeter-days above 20mm	0.178
Cumulative millimeter-days above 30mm	0.430
Cumulative millimeter-days below 1mm	0.582
Cumulative millimeter-days below 0.5mm	0.580
Cumulative millimeter-days below 0.1mm	0.512

Table 4., continued

Variable	P>|t|
Head characteristics	
Weather variables	
Days above the 90th percentile of the temperature distribution	0.282
Days above the 95th percentile of the temperature distribution	0.278
Days above the 99th percentile of the temperature distribution	0.116
Days below the 10th percentile of the temperature distribution	0.969
Days below the 5th percentile of the temperature distribution	0.942
Days below the 1st percentile of the temperature distribution	0.641
Days above the 90th percentile of the rainfall distribution	0.917
Days above the 95th percentile of the rainfall distribution	0.777
Days above the 99th percentile of the rainfall distribution	0.589
Days below the 50th percentile of the rainfall distribution	0.412
Days below the 45th percentile of the rainfall distribution	0.680
Days below the 35th percentile of the rainfall distribution	0.362

Note: OLS with Huber-White standard errors based on two survey rounds (October 1998 and November 1999.) Consumption and income deflated to October 1998 prices. P>|t| is the p-value from tests of randomization. Differences between treatment and control statistically significant at *10%, **5% and ***1%.

Table 5. Impact of Extreme Weather on Household Consumption, by Type of Household

	Poor households				Non-poor households				Wald
	(1)		(2)		(3)		(4)		p-value
Abnormal heat	-0.022	***	-0.017	***	-0.014	**	-0.008		0.231
	(0.004)		(0.003)		(0.006)		(0.006)		
Abnormal cold	-0.019	***	-0.007	**	-0.003		-0.001		0.003
	(0.004)		(0.004)		(0.006)		(0.006)		
Abnormal rainfall	-0.007	***	-0.005	***	-0.004	**	-0.004	***	0.012
	(0.001)		(0.001)		(0.001)		(0.001)		
Abnormal drought	-0.005	***	-0.002	***	-0.002		-0.003	**	0.003
	(0.001)		(0.001)		(0.001)		(0.001)		
Controls	No		Yes		No		Yes		
Number of observations	30,292		26,107		2,554		2,291		

Note: Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. The test of equality of coefficients in columns 1 and 3 is a standard Wald test. Controls include household demographic characteristics as well as characteristics of the head (see text for details.)

Table 6. Impact of Extreme Weather on Household Consumption, by Type of Consumption

	Total consumption				Food consumption				Non-food consumption				Wald test
	(1)		(2)		(3)		(4)		(5)		(6)		*p*-value
Abnormal heat	-0.022	***	-0.017	***	-0.015	***	-0.011	***	-0.045	***	-0.036	***	0.000
	(0.004)		(0.003)		(0.004)		(0.003)		(0.006)		(0.006)		
Abnormal cold	-0.019	***	-0.007	**	-0.016	***	-0.007	*	-0.030	***	-0.010	*	0.015
	(0.004)		(0.004)		(0.004)		(0.004)		(0.006)		(0.006)		
Abnormal rainfall	-0.007	***	-0.005	***	-0.004	***	-0.002	***	-0.015	***	-0.012	***	0.000
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		
Abnormal drought	0.005	***	-0.002	***	-0.003	***	-0.001	**	-0.011	***	-0.005	***	0.000
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		
Controls	No		Yes		No		Yes		No		Yes		
Number of observations	30,292		26,107		30,253		26,075		29,911		25,809		

Note: Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. The test of equality of coefficients in columns 3 and 5 is a standard Wald test. Controls include household demographic characteristics as well as characteristics of the head (see text for details.)

Table 7. Impact of Extreme Weather on Food Consumption, by Constant Pesos Spent and Caloric Consumption

	Total consumption				Food consumption expenses				Caloric intake				Wald test
	(1)		(2)		(3)		(4)		(5)		(6)		*p*-value
Abnormal heat	-0.022	***	-0.017	***	-0.015	***	-0.011	***	-0.001		-0.006	*	0.032
	(0.004)		(0.003)		(0.004)		(0.003)		(0.004)		(0.004)		
Abnormal cold	-0.019	***	-0.007	**	-0.016	***	-0.007	*	-0.019	***	-0.015	***	0.164
	(0.004)		(0.004)		(0.004)		(0.004)		(0.003)		(0.003)		
Abnormal rainfall	-0.007	***	-0.005	***	-0.004	***	-0.002	***	-0.004	***	-0.003	***	0.540
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		
Abnormal drought	0.005	***	-0.002	***	-0.003	***	-0.001	**	0.000		0.002	***	0.000
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		
Controls	No		Yes		No		Yes		No		Yes		
Number of observations	30,292		26,107		30,253		26,075		30,264		26,085		

Note: Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. The test of equality of coefficients in columns 3 and 5 is a standard Wald test. Controls include household demographic characteristics as well as characteristics of the head (see text for details.) Food consumption expenses deflated to October 1998 prices.

Table 8. Impact of Extreme Weather on Household Consumption and Treatment Effect, by Type of Consumption

	Food consumption		Non-food consumption		Wald test
	(1)	(2)	(3)	(4)	p-value
Abnormal heat regression					
Main effect	-0.014 *	-0.014 **	-0.040 ***	-0.029 ***	0.000
	(0.007)	(0.006)	(0.009)	(0.007)	
Treatment	0.130 ***	0.128 ***	0.110 **	0.094 **	
	(0.025)	(0.020)	(0.047)	(0.037)	
Interaction with treatment	-0.007	-0.003	-0.007	-0.010	
	(0.006)	(0.005)	(0.011)	(0.009)	
Abnormal cold regression					
Main effect	-0.016 ***	-0.005	-0.050 ***	-0.026 ***	0.000
	(0.005)	(0.004)	(0.008)	(0.007)	
Treatment	0.119 ***	0.114 ***	0.155 ***	0.129 ***	
	(0.027)	(0.022)	(0.050)	(0.040)	
Interaction with treatment	0.001	-0.002	0.034 ***	0.029 ***	
	(0.007)	(0.006)	(0.010)	(0.010)	

Table 8., continued

	Food consumption				Non-food consumption				Wald test
	(1)		(2)		(3)		(4)		*p*-value
Abnormal rainfall regression									
Main effect	-0.004	***	-0.002		-0.016	***	-0.013	***	0.000
	(0.001)		(0.001)		(0.002)		(0.002)		
Treatment	0.125	***	0.128	***	0.079		0.058		
	(0.032)		(0.026)		(0.055)		(0.043)		
Interaction with treatment	-0.001		-0.001		0.002		0.002		
	(0.002)		(0.001)		(0.003)		(0.002)		
Abnormal drought regression									
Main effect	-0.004	***	-0.002	***	-0.013	***	-0.007	***	0.000
	(0.001)		(0.001)		(0.002)		(0.002)		
Treatment	0.295	**	0.293	***	0.515	**	0.516	**	
	(0.136)		(0.122)		(0.260)		(0.226)		
Interaction with treatment	0.002		0.002		0.004		0.004	*	
	(0.001)		(0.001)		(0.003)		(0.002)		
Controls	No		Yes		No		Yes		
Number of observations	30,253		26,075		29,911		25,809		

Note: Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. The test of equality of coefficients in columns 1 and 3 is a standard Wald test. Controls include household demographic characteristics as well as characteristics of the head (see text for details.)

Table 9. Impact of Extreme Weather on Food Consumption and Treatment Effect, by Constant Pesos Spent and Caloric Consumption

	Food consumption				Caloric intake				Wald test
	(1)		(2)		(3)		(4)		*p*-value
Abnormal heat regression									
Main effect	-0.014	*	-0.014	**	-0.008		-0.007		0.292
	(0.007)		(0.006)		(0.007)		(0.006)		
Treatment	0.130	***	0.128	***	0.099	***	0.093	***	
	(0.025)		(0.020)		(0.019)		(0.017)		
Interaction with treatment	-0.007		-0.003		-0.004		-0.002		
	(0.006)		(0.005)		(0.005)		(0.004)		
Abnormal cold regression									
Main effect	-0.016	***	-0.005		-0.022	***	-0.016	***	0.926
	(0.005)		(0.004)		(0.004)		(0.004)		
Treatment	0.119	***	0.114	***	0.096	***	0.090	***	
	(0.027)		(0.022)		(0.021)		(0.018)		
Interaction with treatment	0.001		-0.002		0.004		0.002		
	(0.007)		(0.006)		(0.006)		(0.006)		

Table 9., continued

	Food consumption (1)		Food consumption (2)		Caloric intake (3)		Caloric intake (4)		Wald test p-value
Abnormal rainfall regression									
Main effect	-0.004	***	-0.002		-0.004	***	-0.003	***	0.608
	(0.001)		(0.001)		(0.001)		(0.001)		
Treatment	0.125	***	0.128	***	0.083	***	0.082	***	
	(0.032)		(0.026)		(0.022)		(0.020)		
Interaction with treatment	-0.001		-0.001		0.000		0.000		
	(0.002)		(0.001)		(0.002)		(0.001)		
Abnormal drought regression									
Main effect	-0.004	***	-0.002	***	-0.001		0.000		0.000
	(0.001)		(0.001)		(0.001)		(0.001)		
Treatment	0.295	**	0.293	***	0.324	***	0.302	***	
	(0.136)		(0.122)		(0.116)		(0.102)		
Interaction with treatment	0.002		0.002		0.002	**	0.002	**	
	(0.001)		(0.001)		(0.001)		(0.001)		
Controls	No		Yes		No		Yes		
Number of observations	30,253		26,075		30,264		26,085		

Note: Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. The test of equality of coefficients in columns 1 and 3 is a standard Wald test. Controls include household demographic characteristics as well as characteristics of the head (see text for details.) Food consumption expenses deflated to October 1998 prices.

Table 10. Impact of Extreme Weather on Household Consumption and Treatment Effect, by Selected Characteristics of the Household Head

	All households				Female			
	(1)		(2)		(3)		(4)	
Abnormal heat regression								
Main effect	-0.013	**	-0.013	**	-0.021	*	-0.022	**
	(0.007)		(0.005)		(0.010)		(0.010)	
Treatment	0.124	***	0.120	***	0.074	*	0.101	***
	(0.027)		(0.020)		(0.038)		(0.033)	
Interaction with treatment	-0.014	**	-0.008	*	-0.009		-0.004	
	(0.006)		(0.004)		(0.008)		(0.008)	
Abnormal cold regression								
Main effect	-0.024	***	-0.010	**	-0.025	***	-0.012	
	(0.005)		(0.004)		(0.009)		(0.008)	
Treatment	0.125	***	0.116	***	0.081	**	0.109	***
	(0.030)		(0.022)		(0.039)		(0.037)	
Interaction with treatment	0.008		0.004		0.012		0.015	
	(0.007)		(0.006)		(0.010)		(0.010)	
Abnormal rainfall regression								
Main effect	-0.007	***	-0.005	***	-0.003		-0.001	
	(0.001)		(0.001)		(0.002)		(0.002)	
Treatment	0.111	***	0.111	***	0.085	*	0.121	***
	(0.033)		(0.025)		(0.046)		(0.040)	
Interaction with treatment	0.000		0.000		-0.003		-0.004	
	(0.002)		(0.001)		(0.003)		(0.003)	
Abnormal drought regression								
Main effect	-0.007	***	-0.004	***	-0.004	**	-0.003	
	(0.001)		(0.001)		(0.002)		(0.002)	
Treatment	0.345	**	0.343	***	0.239		0.396	*
	(0.148)		(0.126)		(0.248)		(0.234)	
Interaction with treatment	0.002		0.002	**	0.002		-0.003	
	(0.001)		(0.001)		(0.002)		(0.002)	
Controls	No		Yes		No		Yes	
Number of observations	30,292		26,107		3,170		2,538	

Table 10., continued

	Senior				Indigenous			
	(5)		(6)		(7)		(8)	
Abnormal heat regression								
Main effect	-0.004		-0.006		-0.025	***	-0.026	***
	(0.008)		(0.007)		(0.009)		(0.008)	
Treatment	0.102	***	0.086	***	0.215	***	0.204	***
	(0.032)		(0.025)		0.042		(0.040)	
Interaction with treatment	-0.013	*	-0.001		0.002		0.000	
	(0.007)		(0.006)		(0.007)		(0.006)	
Abnormal cold regression								
Main effect	-0.020	***	-0.005		-0.039	***	-0.035	***
	(0.006)		(0.006)		(0.006)		(0.006)	
Treatment	0.116	***	0.099	***	0.156	***	0.147	***
	(0.034)		(0.028)		(0.037)		(0.036)	
Interaction with treatment	0.011		0.014		-0.002		-0.004	
	(0.009)		(0.009)		(0.011)		(0.010)	
Abnormal rainfall regression								
Main effect	-0.007	***	-0.004	**	0.000		-0.001	
	(0.002)		(0.002)		(0.002)		(0.002)	
Treatment	0.082	**	0.068	**	0.251	***	0.256	***
	(0.037)		(0.030)		(0.071)		(0.066)	
Interaction with treatment	0.001		0.001		-0.005		-0.006	**
	(0.002)		(0.002)		(0.003)		(0.003)	
Abnormal drought regression								
Main effect	-0.006	***	-0.003	**	-0.003		-0.002	
	(0.001)		(0.001)		(0.003)		(0.003)	
Treatment	0.363	**	0.344	**	0.655	*	0.529	
	(0.182)		(0.160)		(0.347)		(0.350)	
Interaction with treatment	0.003		0.003	*	-0.005		0.004	
	(0.002)		(0.002)		(0.004)		(0.004)	
Controls	No		Yes		No		Yes	
Number of observations	4,292		3,791		10,512		10,501	

Table 10., continued

	Illiterate				Unemployed			
	(9)		(10)		(11)		(12)	
Abnormal heat regression								
Main effect	-0.014	*	-0.014	**	-0.007		-0.004	
	(0.004)		(0.006)		(0.010)		(0.009)	
Treatment	0.119	***	0.120	***	0.107	***	0.110	***
	(0.026)		(0.020)		(0.034)		(0.030)	
Interaction with treatment	-0.019	***	-0.010	**	-0.021	**	-0.011	
	(0.006)		(0.005)		(0.009)		(0.008)	
Abnormal cold regression								
Main effect	-0.019	***	-0.007		-0.018	***	-0.004	
	(0.005)		(0.004)		(0.007)		(0.006)	
Treatment	0.111	***	0.105	***	0.112	***	0.122	***
	(0.031)		(0.022)		(0.038)		(0.033)	
Interaction with treatment	0.002		-0.002		0.004		0.008	
	(0.007)		(0.006)		(0.009)		(0.009)	
Abnormal rainfall regression								
Main effect	-0.009	***	-0.005	***	-0.005	**	-0.002	
	(0.001)		(0.001)		(0.002)		(0.002)	
Treatment	0.104	***	0.114	***	0.110	***	0.127	***
	(0.027)		(0.023)		(0.041)		(0.034)	
Interaction with treatment	0.000		-0.001		-0.002		-0.002	
	(0.002)		(0.001)		(0.003)		(0.002)	
Abnormal drought regression								
Main effect	-0.007	***	-0.003	***	-0.005	***	-0.002	
	(0.001)		(0.001)		(0.001)		(0.002)	
Treatment	0.298	*	0.251	**	0.342		0.391	**
	(0.159)		(0.128)		(0.212)		(0.197)	
Interaction with treatment	0.002		0.001		0.002		0.003	
	(0.001)		(0.001)		(0.002)		(0.002)	
Controls	No		Yes		No		Yes	
Number of observations	17,500		17,471		3,902		3,291	

Table 10., continued

	Farmer		Landless		Wald test
	(13)	(14)	(15)	(16)	*p*-value
Abnormal heat regression					
Main effect	-0.017 ***	-0.017 ***	-0.011 *	-0.012 **	0.016
	(0.006)	(0.005)	(0.006)	(0.006)	
Treatment	0.150 ***	0.141 ***	0.107 ***	0.107 ***	
	(0.026)	(0.021)	(0.032)	(0.024)	
Interaction with treatment	-0.013 **	-0.008 *	-0.008 *	-0.006	
	(0.005)	(0.004)	(0.004)	(0.005)	
Abnormal cold regression					
Main effect	-0.020 ***	-0.008 **	-0.022 ***	-0.013 ***	0.001
	(0.005)	(0.004)	(0.005)	(0.005)	
Treatment	0.142 ***	0.125 ***	0.113 ***	0.108 ***	
	(0.029)	(0.023)	(0.034)	(0.027)	
Interaction with treatment	-0.004	-0.001	0.009	0.006	
	(0.007)	(0.007)	(0.007)	(0.007)	
Abnormal rainfall regression					
Main effect	-0.006 ***	-0.004 ***	-0.007 ***	-0.006 ***	0.076
	(0.001)	(0.001)	(0.001)	(0.001)	
Treatment	0.141 ***	0.137 ***	0.093 ***	0.098 ***	
	(0.033)	(0.027)	(0.035)	(0.027)	
Interaction with treatment	-0.001	-0.001	0.000	0.000	
	(0.002)	(0.001)	(0.002)	(0.002)	
Abnormal drought regression					
Main effect	-0.005 ***	-0.002 **	-0.006 ***	-0.004 ***	0.399
	(0.001)	(0.001)	(0.001)	(0.001)	
Treatment	0.212	0.203	0.325 *	0.364 **	
	(0.158)	(0.141)	(0.185)	(0.157)	
Interaction with treatment	0.001	0.001	0.002	0.003 *	
	(0.001)	(0.001)	(0.002)	(0.001)	
Controls	No	Yes	No	Yes	
Number of observations	18,006	15,797	11,591	9,713	

Note: Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. The test of equality of coefficients is a standard Wald test. Controls include household demographic characteristics as well as characteristics of the head (see text for details.)

Table 11. Impact of Extreme Weather on Household Consumption and Treatment Effect, by Weather Event

	El Niño				La Niña				Wald test
	(1)		(2)		(3)		(4)		p-value
Abnormal heat regression									
Main effect	-0.012	*	-0.012	**	-0.051		-0.061		0.195
	(0.007)		(0.006)		(0.051)		(0.037)		
Treatment	0.124	***	0.120	***	0.130	***	0.129	***	
	(0.034)		(0.029)		(0.030)		(0.023)		
Interaction with treatment	-0.012	**	-0.008	*	-0.062		-0.042		
	(0.005)		(0.004)		(0.041)		(0.028)		
Abnormal cold regression									
Main effect	-0.028	***	-0.015	***	-0.016	**	-0.003		0.118
	(0.005)		(0.004)		(0.006)		(0.005)		
Treatment	0.115	***	0.105	***	0.131	***	0.124	***	
	(0.036)		(0.031)		(0.032)		(0.024)		
Interaction with treatment	0.008		0.004		0.009		0.008		
	(0.008)		(0.007)		(0.009)		(0.008)		
Abnormal rainfall regression									
Main effect	-0.006	***	-0.004	***	-0.008	***	-0.005	***	0.554
	(0.002)		(0.001)		(0.002)		(0.001)		
Treatment	0.091	**	0.084	**	0.124	***	0.130	***	
	(0.045)		(0.037)		(0.033)		(0.026)		
Interaction with treatment	0.001		0.001		-0.001		-0.001		
	(0.002)		(0.002)		(0.002)		(0.002)		
Abnormal drought regression									
Main effect	-0.007	***	-0.003	**	-0.006	***	-0.004	***	0.912
	(0.002)		(0.001)		(0.001)		(0.001)		
Treatment	0.517	**	0.558	***	0.278	*	0.259	*	
	(0.211)		(0.190)		(0.161)		(0.138)		
Interaction with treatment	-0.004	**	0.005	**	0.002		0.001		
	(0.002)		(0.002)		(0.001)		(0.001)		
Controls	No		Yes		No		Yes		
Number of observations	12,887		11,042		17,405		15,065		

Note: Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. The test of equality of coefficients in columns 1 and 3 is a standard Wald test. Controls include household demographic characteristics as well as characteristics of the head (see text for details.)

Table 12. Impact of Extreme Weather on Welfare, by Type of Shock

	Arable land loss				Harvest loss				Home loss			
	(1)		(2)		(3)		(4)		(5)		(6)	
Abnormal heat	0.001		0.001		0.018	***	0.014	***	0.000		0.000	
	(0.001)		(0.001)		(0.004)		(0.004)		(0.000)		(0.000)	
Abnormal cold	0.003	***	0.003	***	0.026	***	0.032	***	-0.0004	**	-0.001	**
	(0.001)		(0.001)		(0.003)		(0.003)		(0.000)		(0.000)	
Abnormal rainfall	0.001	***	0.001	***	0.004	***	0.004	***	0.0001	**	0.000	
	(0.000)		(0.000)		(0.001)		(0.000)		(0.001)		(0.000)	
Abnormal drought	0.001	***	0.001	***	0.004	***	0.004	***	0.0003	***	0.0004	***
	(0.000)		(0.000)		(0.001)		(0.001)		(0.000)		(0.000)	
Controls	No		Yes		No		Yes		No		Yes	
Number of observations	33,681		26,131		33,681		26,131		33,681		26,131	

Table 12., continued

	Hardware loss				Death		Cattle death loss			
	(7)		(8)		(9)	(10)	(11)		(12)	
Abnormal heat	0.000		0.000		0.000	0.000	0.000		0.000	
	(0.000)		(0.000)		(0.000)	(0.000)	(0.001)		(0.000)	
Abnormal cold	0.000		0.000		0.000	0.000	-0.003	***	-0.004	***
	(0.000)		(0.000)		(0.000)	(0.000)	(0.000)		(0.001)	
Abnormal rainfall	0.000		0.000		0.000	0.000	0.000		0.000	
	(0.000)		(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	
Abnormal drought	0.0003	**	0.0003	**	0.000	0.000	0.000		0.000	
	(0.000)		(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	
Controls	No		Yes		No	Yes	No		Yes	
Number of observations	33,681		26,131		33,681	26,131	33,681		26,131	

Note: Average marginal effects ($\partial F/\partial x$) on the probability of a household experiencing a material or human life loss, conditional on being hit by a weather shock. * significant at 10%; ** significant at 5%; *** significant at 1%. Probit estimation with robust standard errors. Each model includes a full set of time-varying household characteristics (see text for details.)

Table 13. OLS Estimates of Double Log Calorie Intake and Calorie Price Regressions (Calorie Engel Curves)

	Log caloric intake						Log price per calorie					
	Pooled		Treatment		Control		Pooled		Treatment		Control	
	(1)		(2)		(3)		(4)		(5)		(6)	
Panel A. OLS estimates												
Log p.a.e. food consumption	0.589	***	0.573	***	0.618	***	0.411	***	0.427	***	0.382	***
	(0.021)		(0.028)		0.028		(0.021)		(0.028)		(0.028)	
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Number of observations	26075		15549		10526		26075		15549		10526	
R^2	0.502		0.509		0.489		0.423		0.414		0.450	
Panel B. OLS estimates (full time effects, non-linear case)												
Log p.a.e. food consumption	0.600	***	0.583	***	0.623	***	0.403	***	0.417	***	0.377	***
	(0.020)		(0.027)		(0.028)		(0.020)		(0.027)		(0.028)	
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Number of observations	26075		15549		10526		26075		15549		10526	
R^2	0.506		0.516		0.491		0.431		0.423		0.452	
Panel C. OLS estimates (intercept shifts only, non-linear case)												
Log p.a.e. food consumption	0.538	***	0.550	***	0.520	***	0.462	***	0.449	***	0.480	***
	(0.013)		(0.016)		(0.021)		(0.013)		(0.016)		(0.021)	
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Number of observations	26075		15549		10526		26075		15549		10526	
R^2	0.500		0.513		0.480		0.424		0.419		0.440	

Note: p.a.e.=per adult equivalent. Huber-White standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Additional regressors not reported include village fixed-effects, time fixed-effects and a vector of time-varying household characteristics including household demographic characteristics and characteristics of the head.

Table 14. Calibration of Marginal Welfare Gains of Program Recipience

Model	$\Delta c/c$	ROO[1]	C	PC	OR[1]	R
Abnormal heat	0.12	0.14	0.24	0.27	0.28	0.32
Abnormal cold	0.12	0.14	0.23	0.26	0.27	0.31
Abnormal rainfall	0.11	0.13	0.22	0.25	0.26	0.30
Abnormal drought	0.34	0.41	0.69	0.77	0.79	0.93

Note: Based on the coefficients of risk aversion estimated by Reinhart, Ogaki & Ostry [ROO] (1996), Cho [C] (2005), Pavan & Colussi [PC] (2008), Ostry & Reinhart [OR] (1992) and Rossi [R] (1988.) $\Delta c/c$ is the estimated raw treatment effect on total consumption per adult equivalent from model specifications including a vector of time-varying household demographic characteristics as well as characteristics of the head. (1): Lower-bound estimates considered.

Map A: Private insurance

Map B: Federal crop insurance

Figure 1. Municipalities with crop insurance in Mexico, by provider, 2010
Source: Agroasemex (2010)

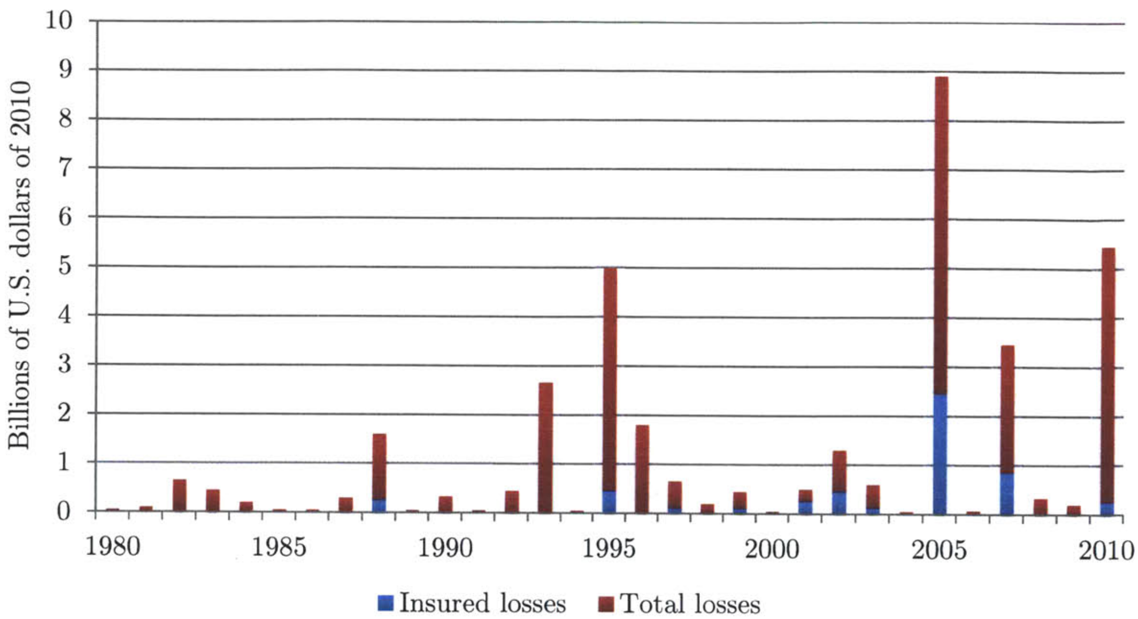


Figure 2. Total and insured losses caused by natural disasters in Mexico, 1980-2010
Source: Münchener Rückversicherungs-Gesellschaft, Geo Risks Research, NatCatSERVICE.

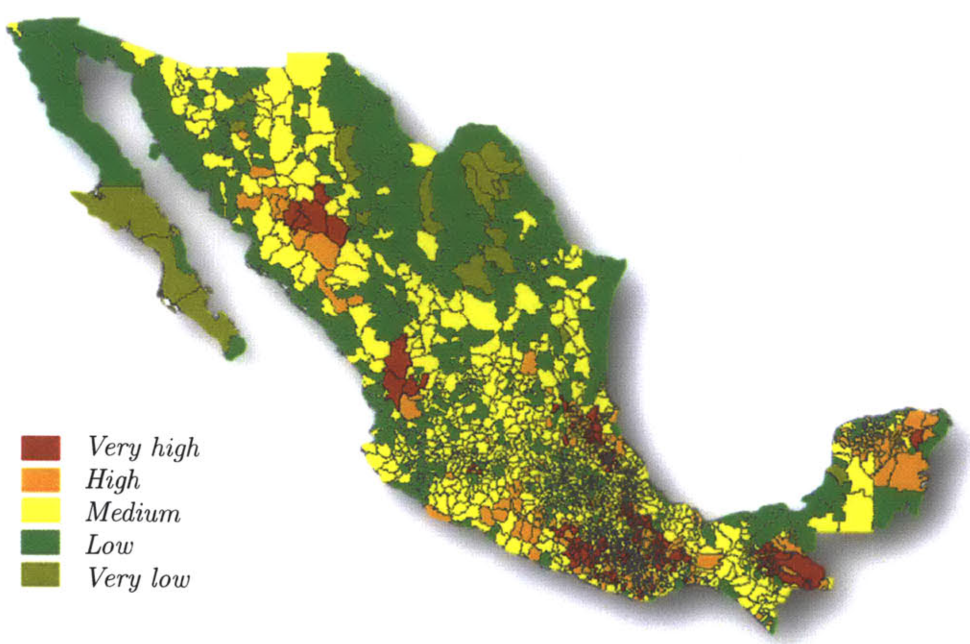


Figure 3. Climate vulnerability, by municipality
Source: Centro Nacional de Prevención de Desastres (2012)

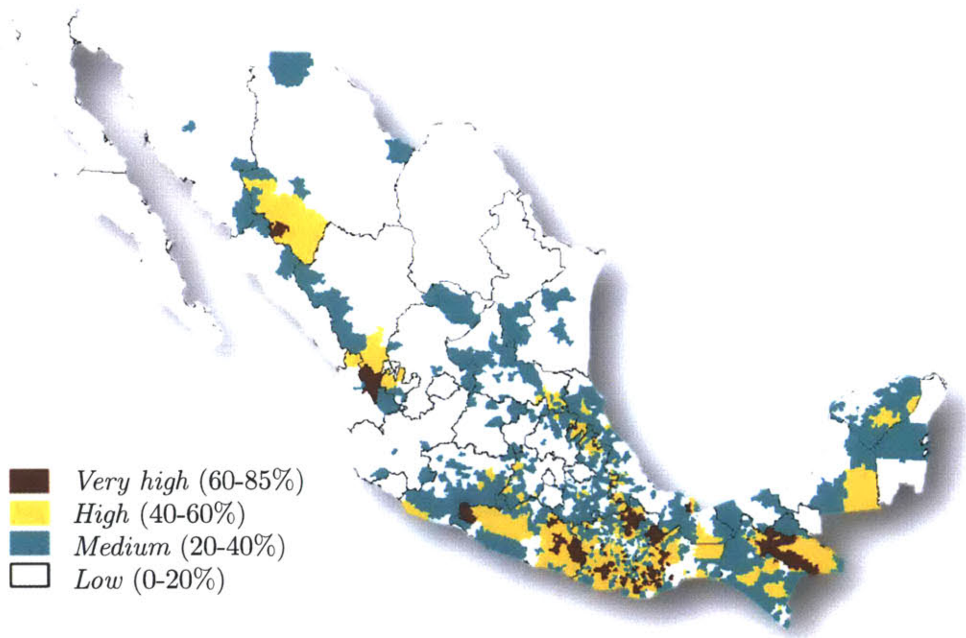


Figure 4. Percentage of the population in extreme poverty, by municipality, 2010

Source: Consejo Nacional de Evaluación de la Política de Desarrollo Social (2011, 2013)
Note: An approximate 2 (3) dollar per person per day threshold for extreme poverty was the standard adopted by the Mexican government for rural (urban) areas (in 2010 US prices).

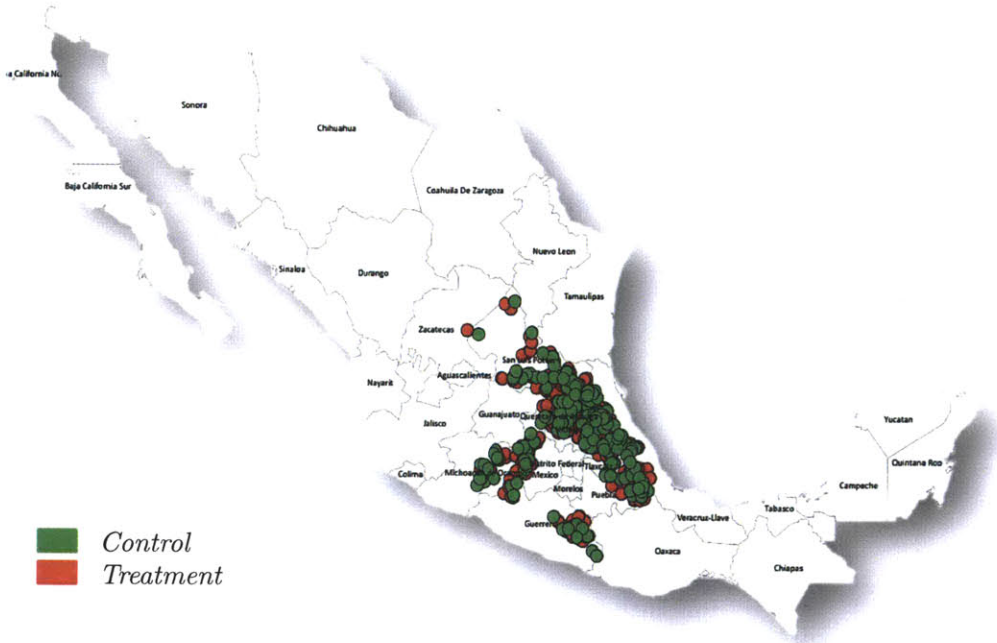
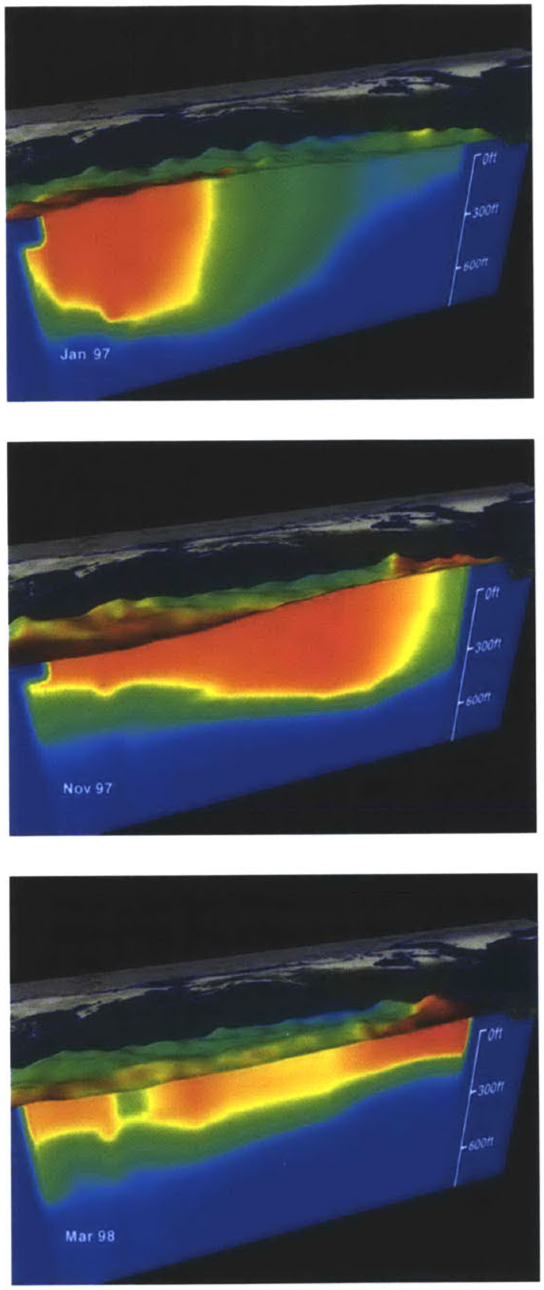


Figure 5. Recipient and non-recipient localities selected for the Progresa impact evaluation

Source: Teele, Kumar and Shroff (2009)



A.

B.

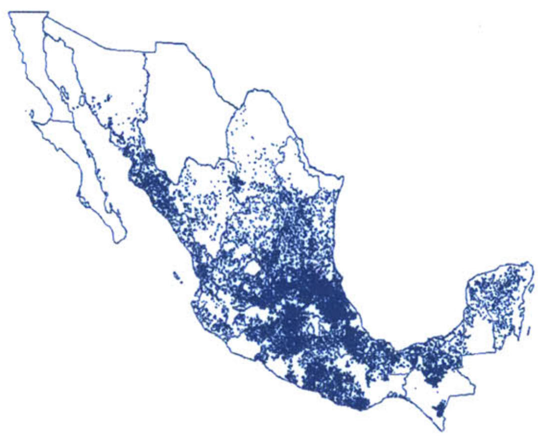
C.

Figure 6. A three-dimensional sea level and surface temperature profile, Equatorial Pacific Ocean

Notes: Sea surface height is represented by the bumps. Red is 30°C and blue is 8°C. Panel A illustrates sea temperature conditions before El Niño started (January 1997.) Panel B. shows how sea temperature increases as a result of El Niño episode of 1997 (November), while Panel C. presents the cooling effect caused by the development of La Niña in early1998 (March.) Source: NASA Goddard Space Center, reproduced in NOAA (2013.)

Map A. August 1997: 300,000 households in 6,344 localities

Map B. August 1998: 1.6 million households in 40,711 localities



Map C. September 1999: 2.3 million households in 53,152 localities

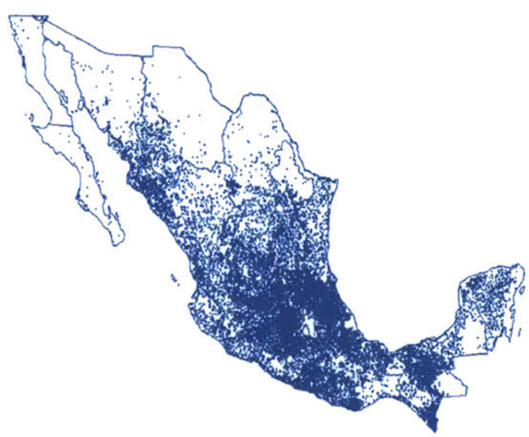


Figure 7. Progresa coverage (proliferation of beneficiary localities), 1997-1999
Source: Levy (2006), Ministry of Social Development (1999)

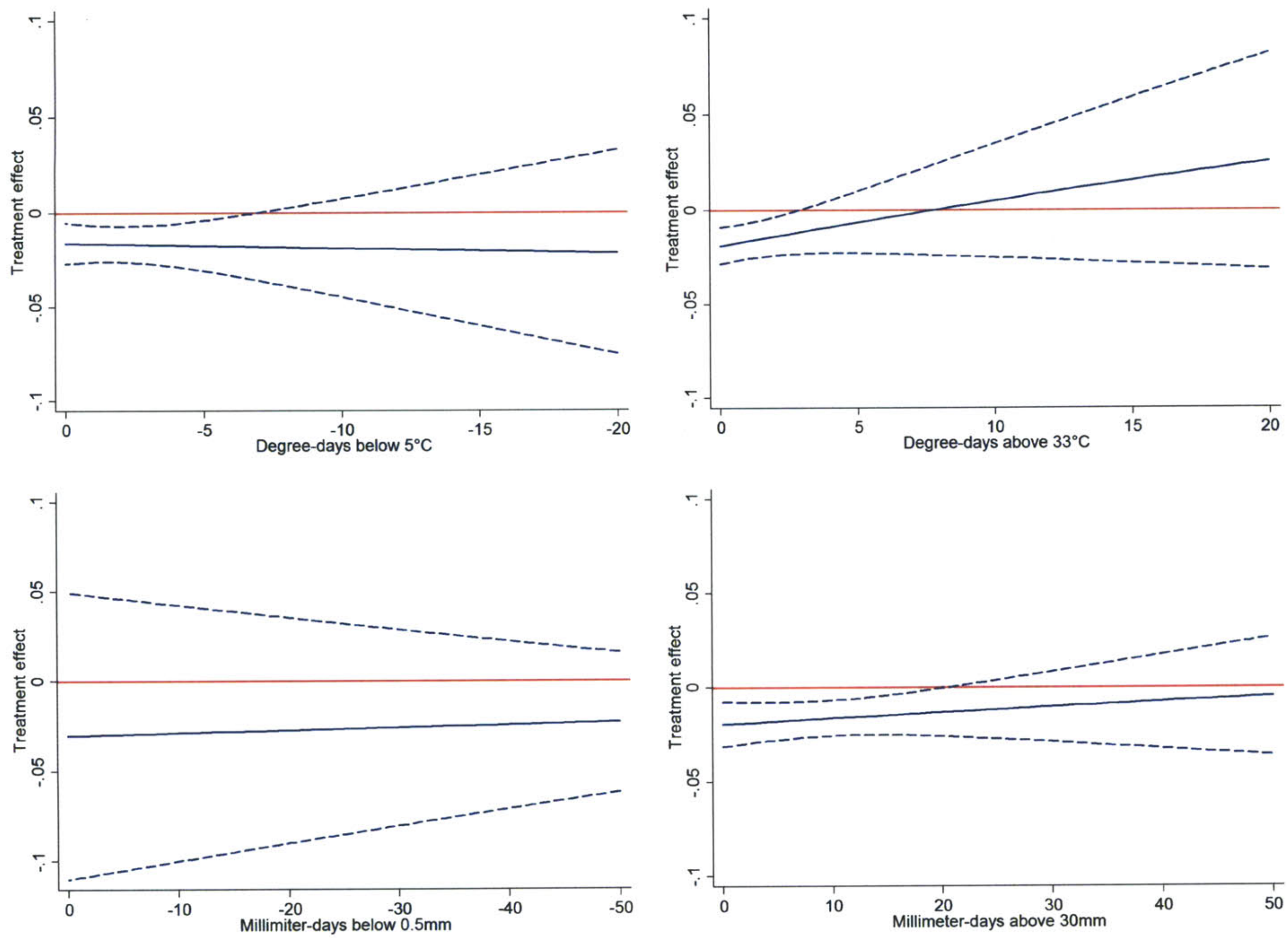


Figure 8. Average marginal program effects ($(\partial F/\partial x)$ with 95% confidence intervals) on the probability of the household sending children to work to cope with a weather shock, by type and intensity of shock. Probit estimation with robust standard errors. Each model includes a full set of time-varying household characteristics (see text for details.)

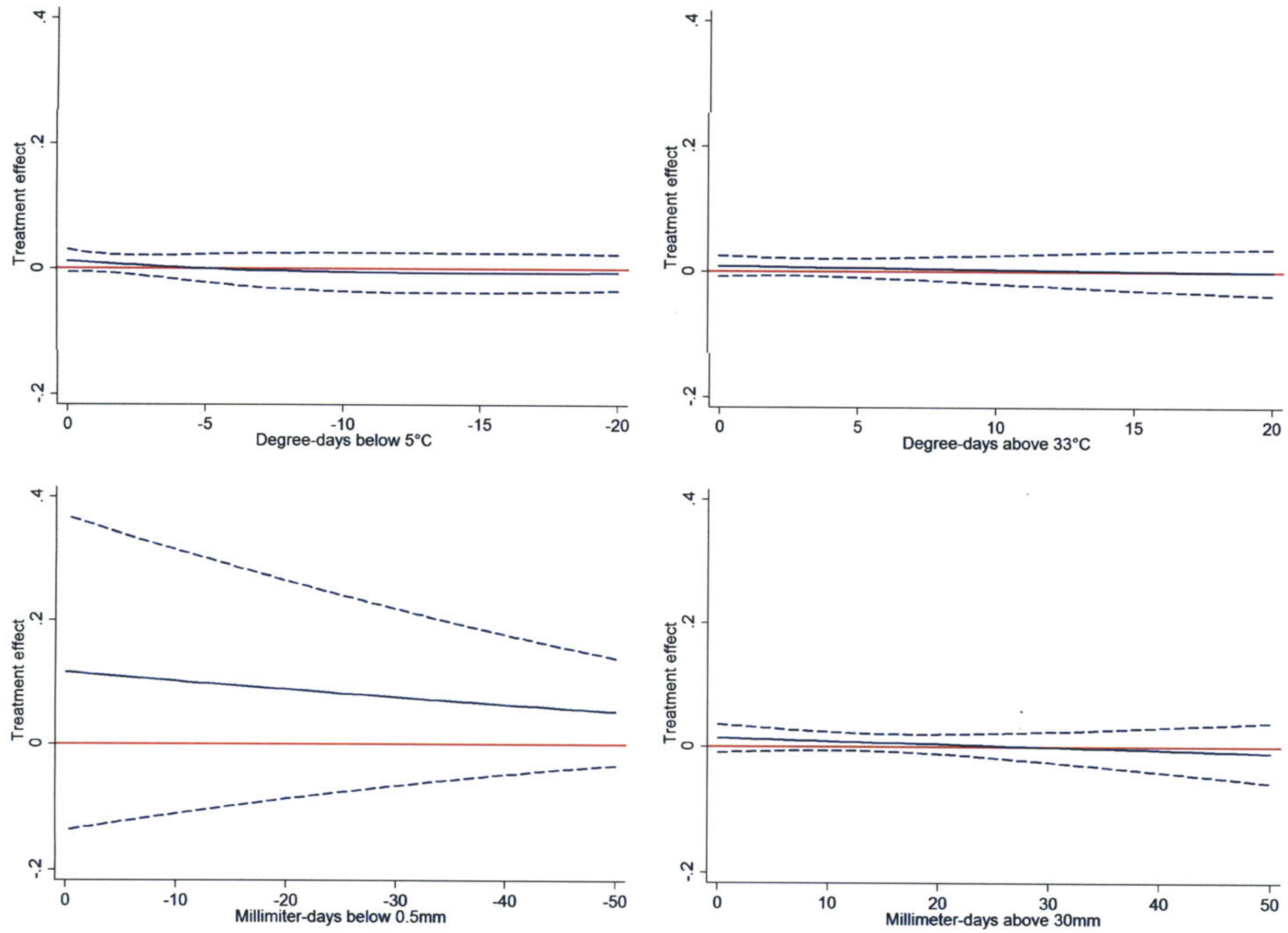


Figure 9. Average marginal program effects ($(\partial F/\partial x)$ with 95% confidence intervals) on the probability of the household diversifying crop production to cope with a weather shock, by type and intensity of shock. Probit estimation with robust standard errors. Each model includes a full set of time-varying household characteristics (see text for details.)

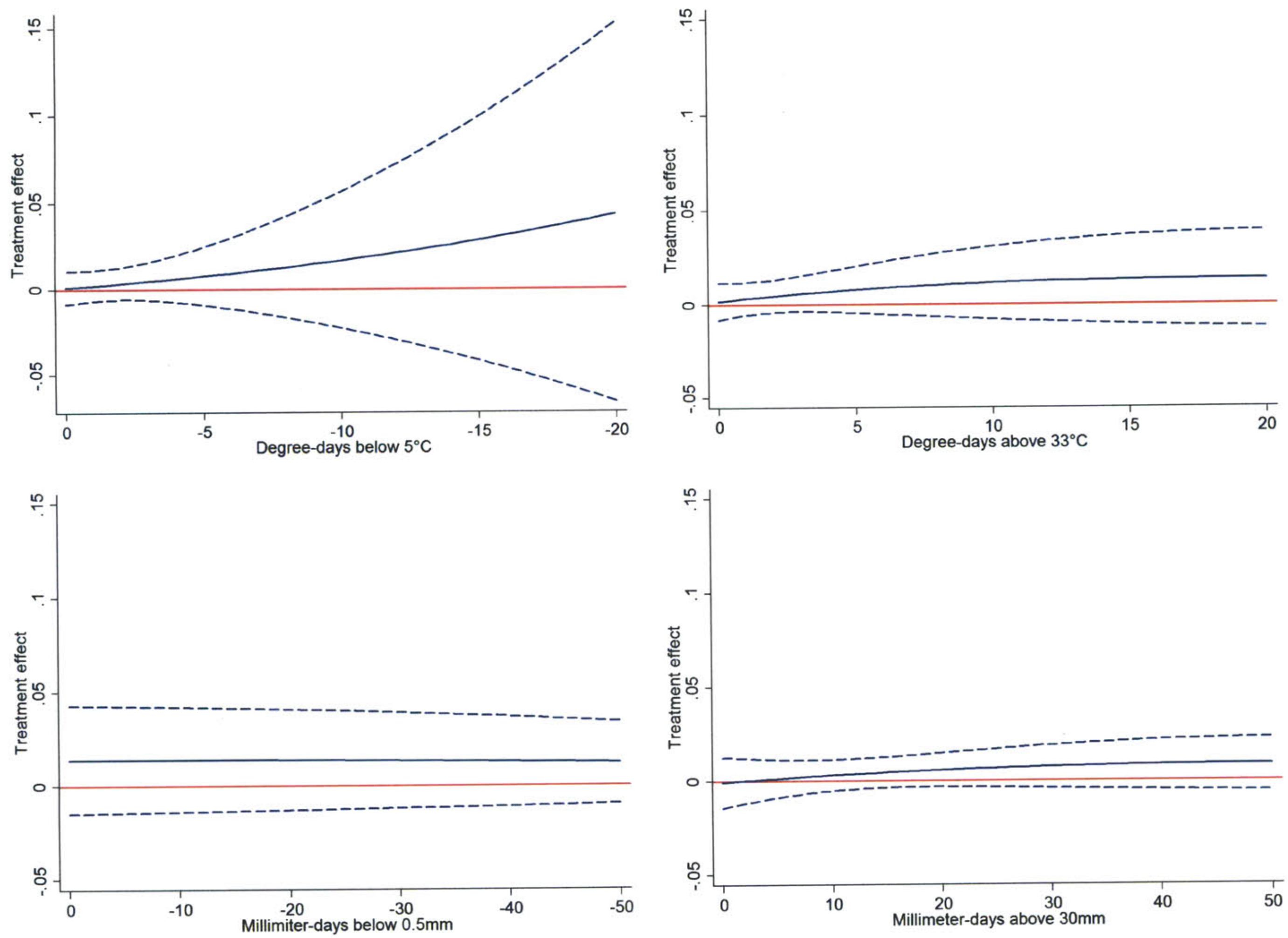


Figure 10. Average marginal program effects $((\partial F/\partial x)$ with 95% confidence intervals) on the probability of the household selling cattle to cope with a weather shock, by type and intensity of shock. Probit estimation with robust standard errors. Each model includes a full set of time-varying household characteristics (see text for details.)

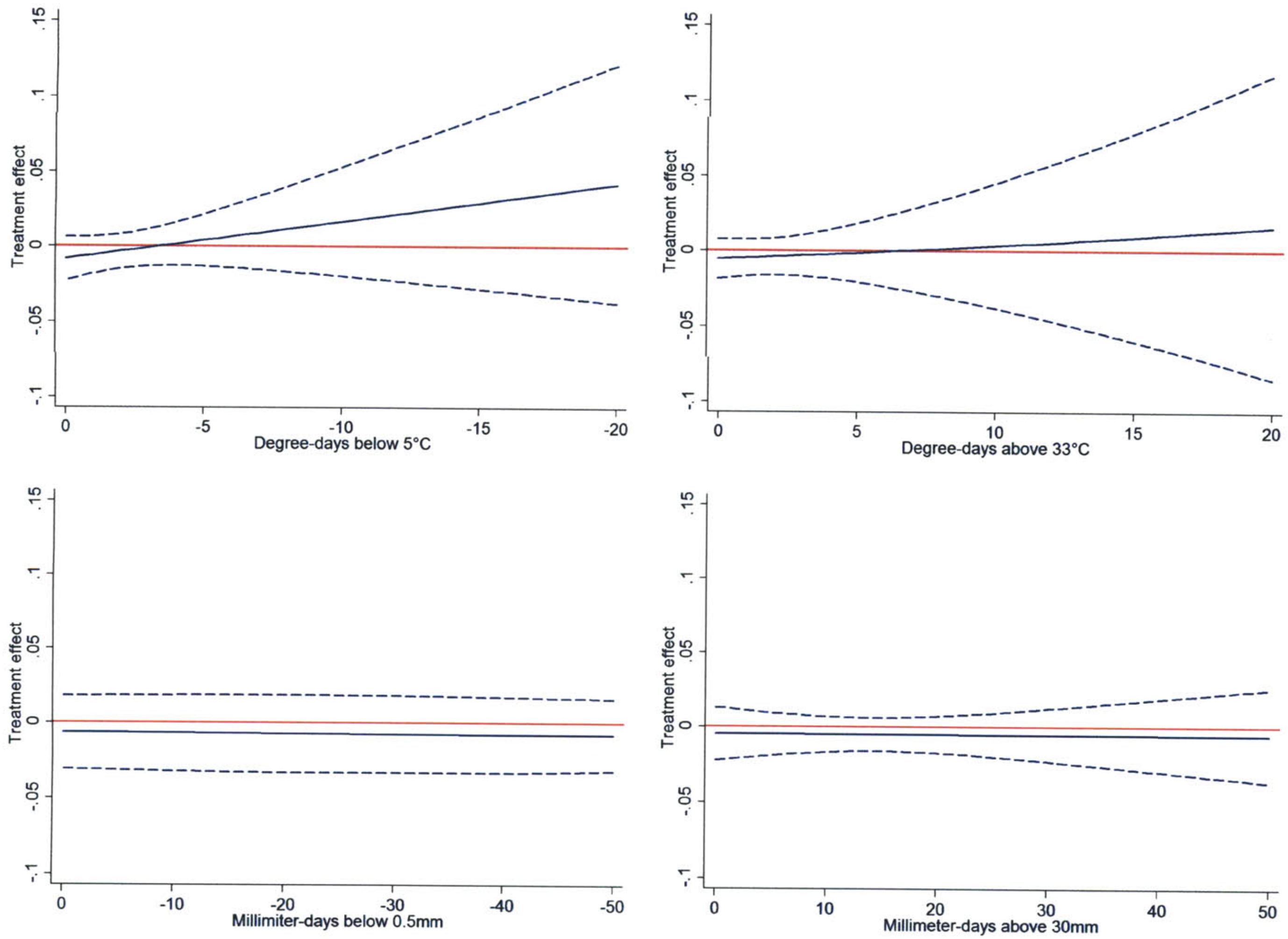


Figure 11. Average marginal program effects ($(\partial F/\partial x)$ with 95% confidence intervals) on the probability of the household adjusting their labor supply (working more hours) to cope with a weather shock, by type and intensity of shock. Probit estimation with robust standard errors. Each model includes a full set of time-varying household characteristics (see text for details.)

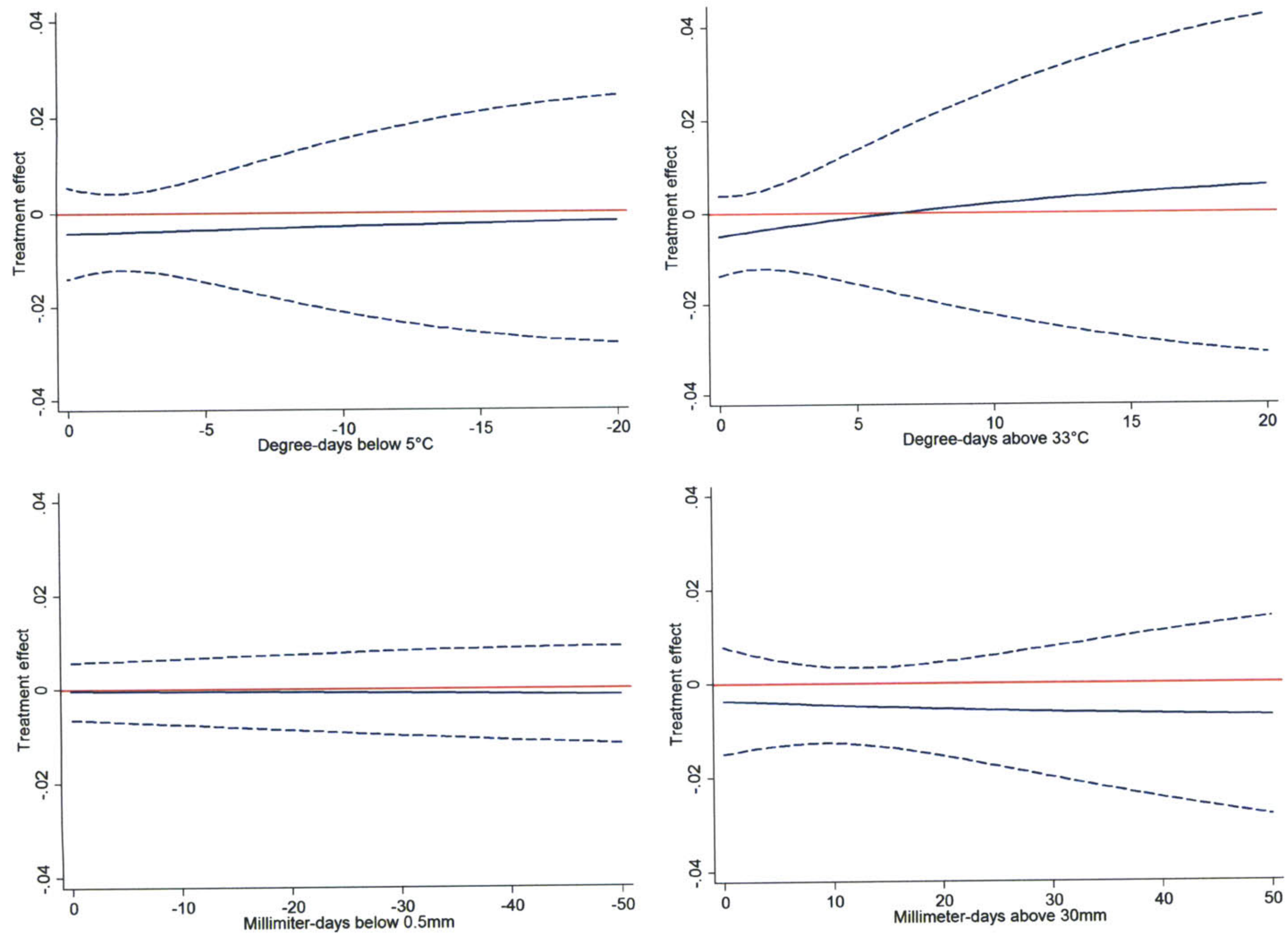


Figure 12. Average marginal program effects ($(\partial F/\partial x)$ with 95% confidence intervals) on the probability of the household receiving family aid to cope with a weather shock, by type and intensity of shock. Probit estimation with robust standard errors. Each model includes a full set of time-varying household characteristics (see text for details.)

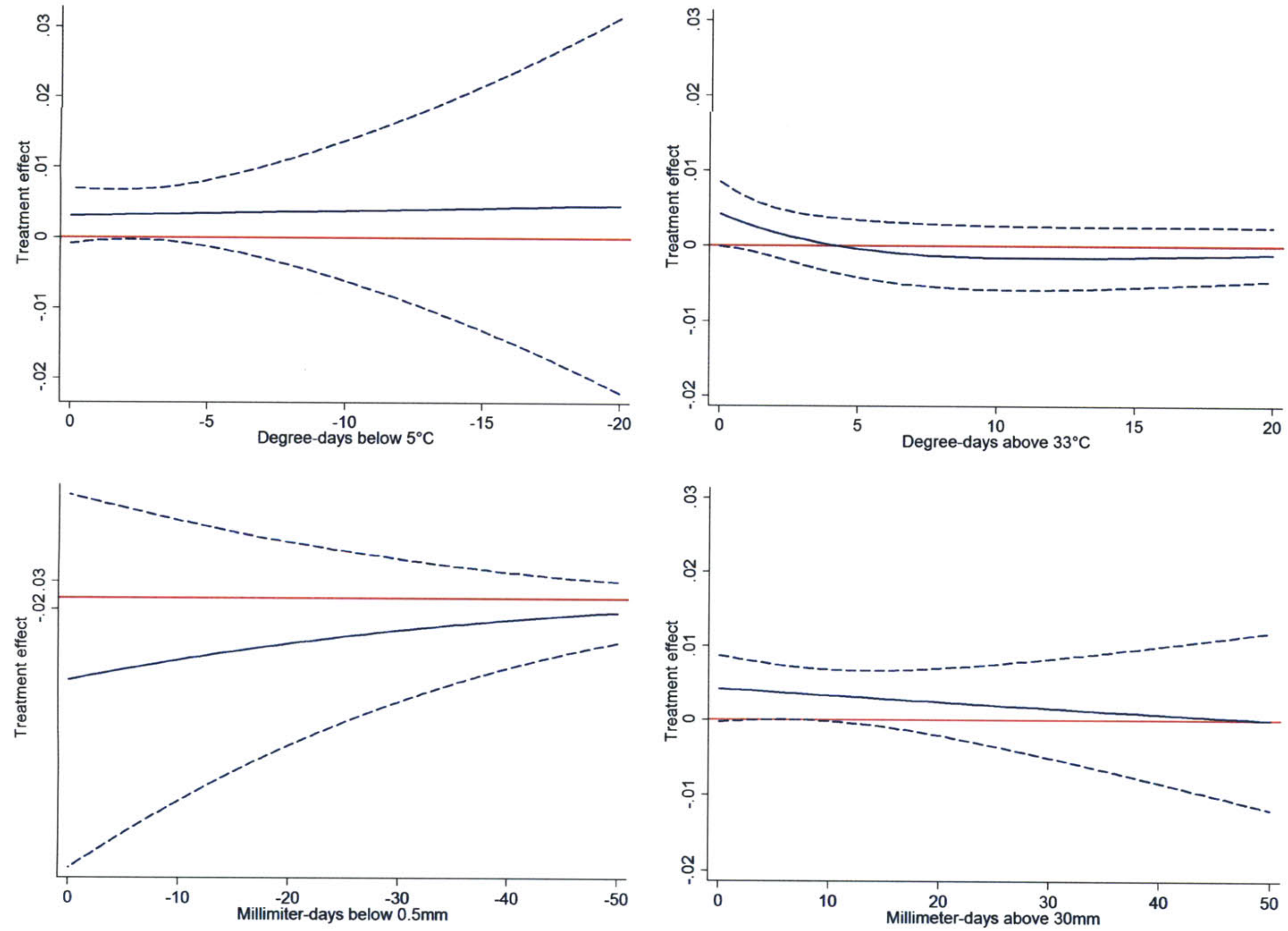


Figure 13. Average marginal program effects (($\partial F/\partial x$) with 95% confidence intervals) on the probability of at least one household member migrating to another town within their municipality of residence to cope with a weather shock, by type and intensity of shock. Probit estimation with robust standard errors. Each model includes a full set of time-varying household characteristics (see text.)

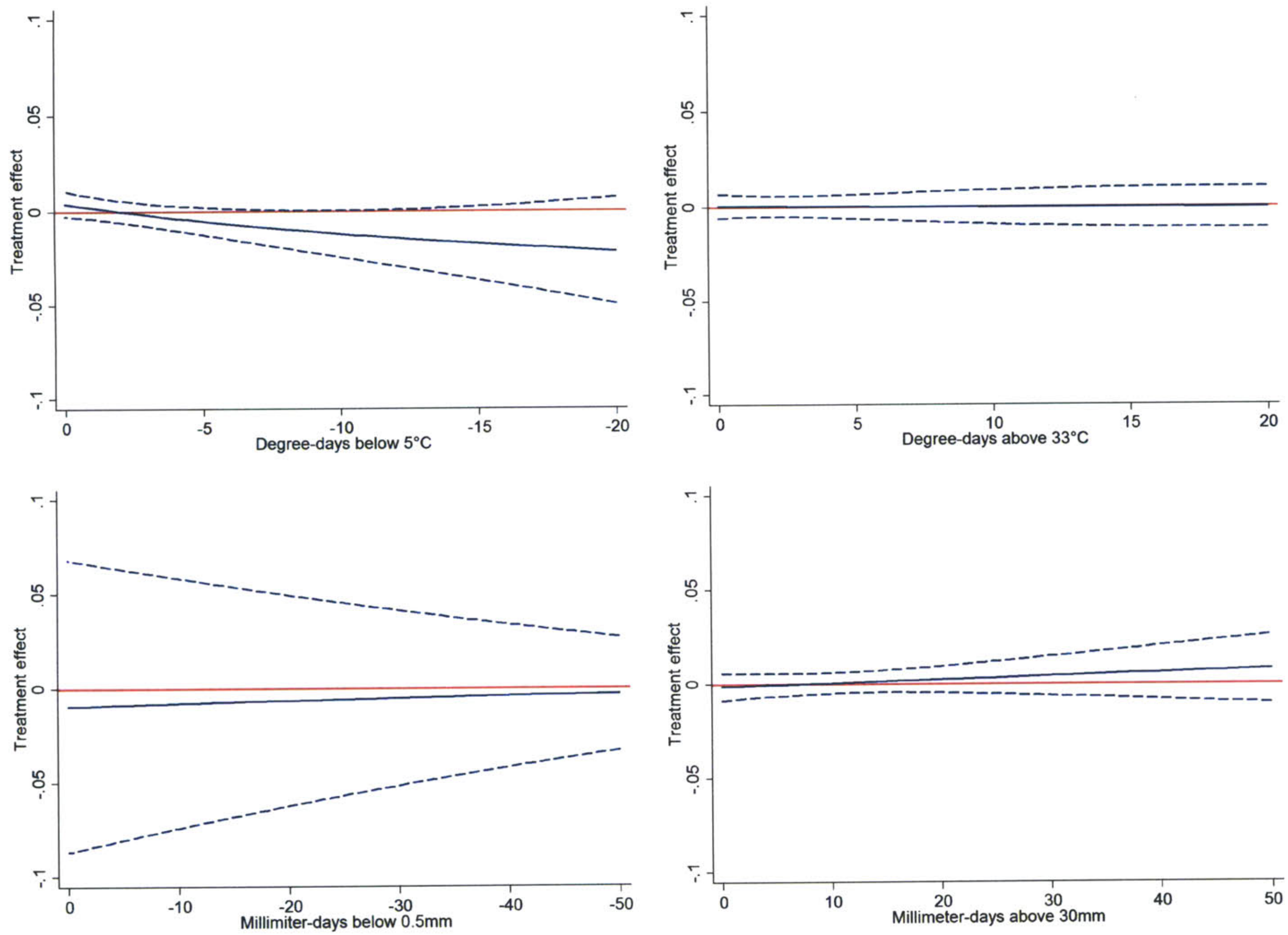


Figure 14. Average marginal program effects ($(\partial F/\partial x)$ with 95% confidence intervals) on the probability of at least one household member migrating to another village within their state of residence to cope with a weather shock, by type and intensity of shock. Probit estimation with robust standard errors. Each model includes a full set of time-varying household characteristics (see text for details.)

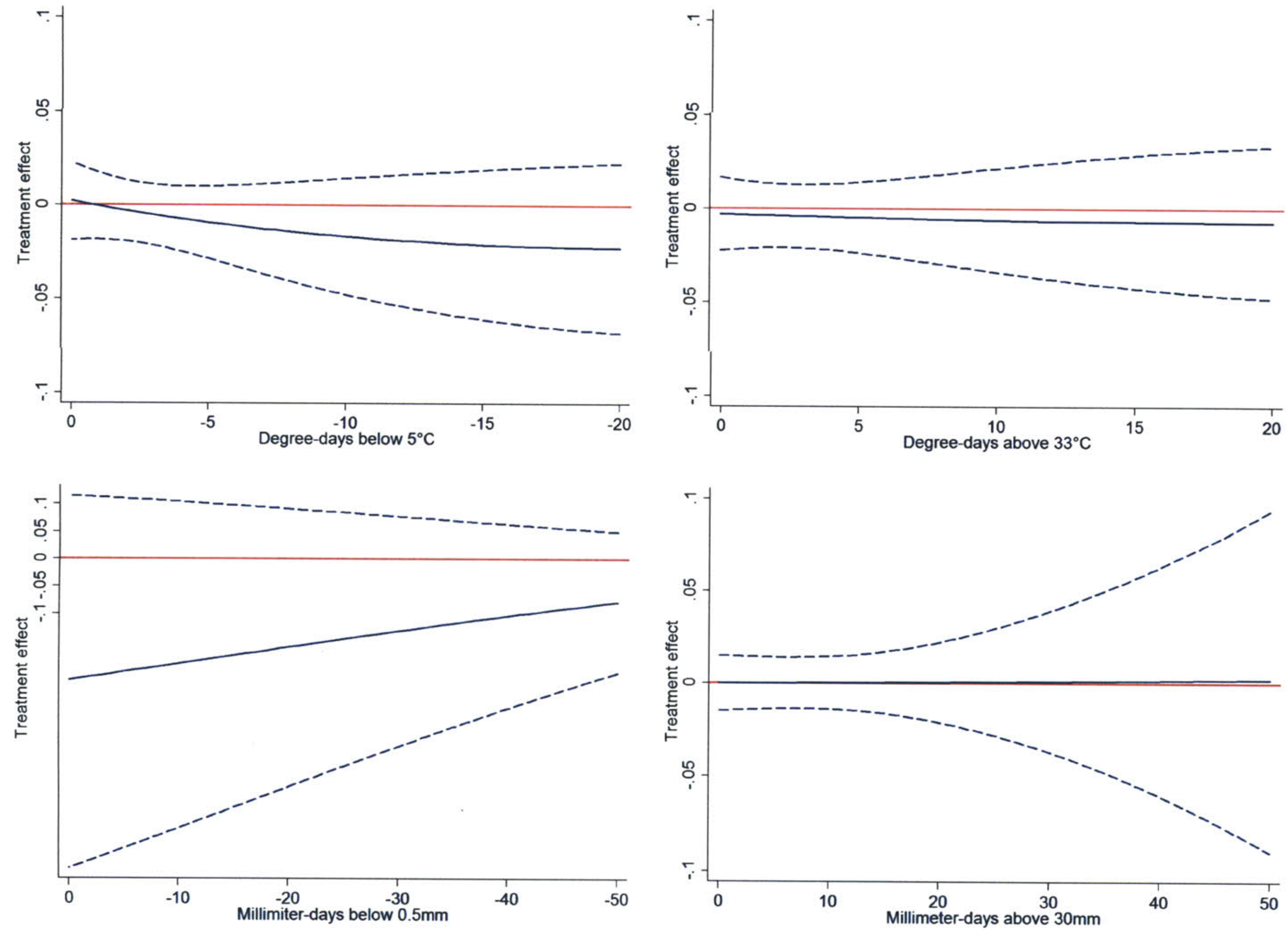


Figure 15. Average marginal program effects (($\partial F/\partial x$) with 95% confidence intervals) on the probability of at least one household member migrating to another state to cope with a weather shock, by type and intensity of shock. Probit estimation with robust standard errors. Each model includes a full set of time-varying household characteristics (see text for details.)

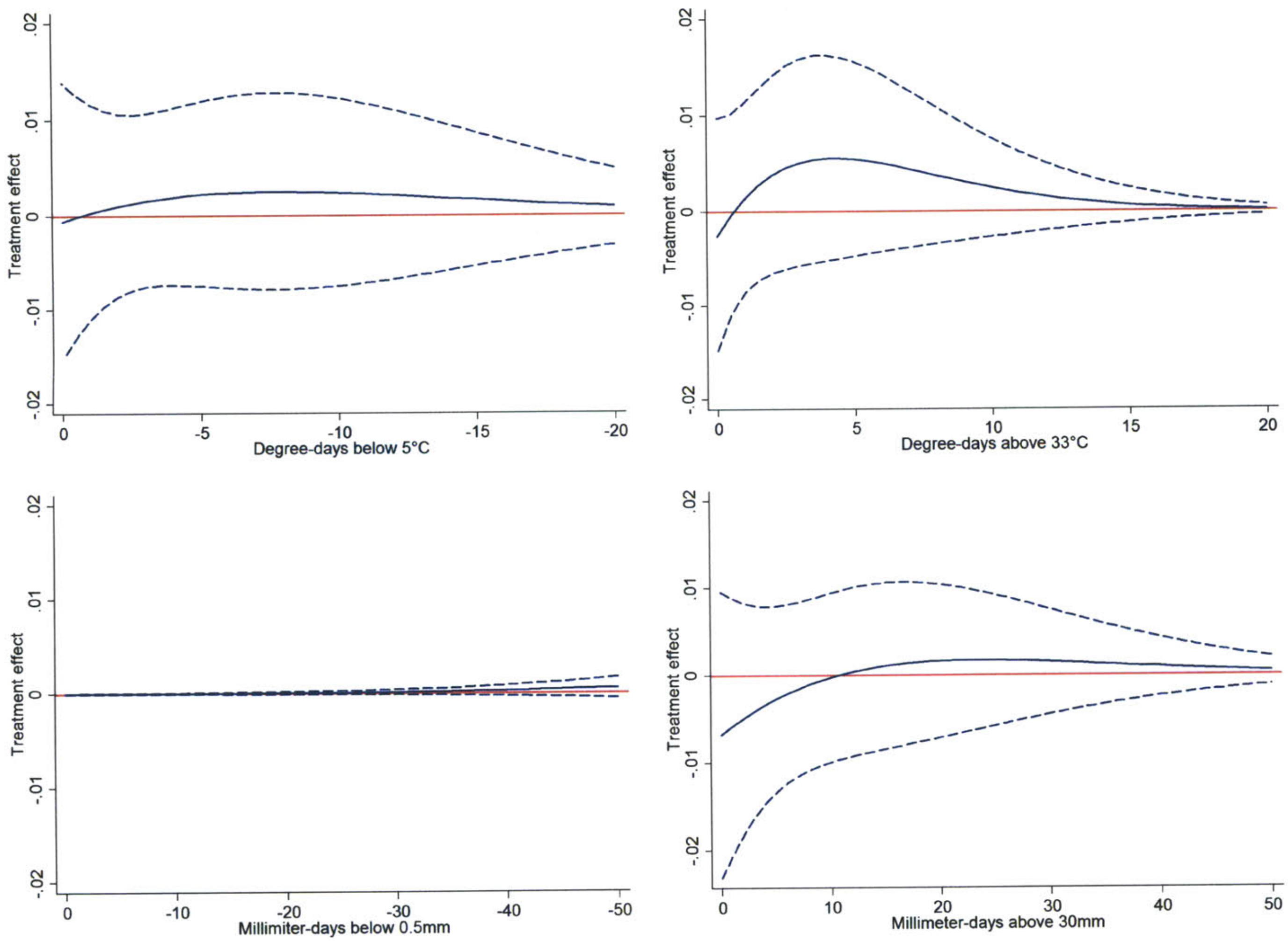


Figure 16. Average marginal program effects (($\partial F/\partial x$) with 95% confidence intervals) on the probability of at least one household member migrating to the United States to cope with a weather shock, by type and intensity of shock. Probit estimation with robust standard errors. Each model includes a full set of time-varying household characteristics (see text for details.)

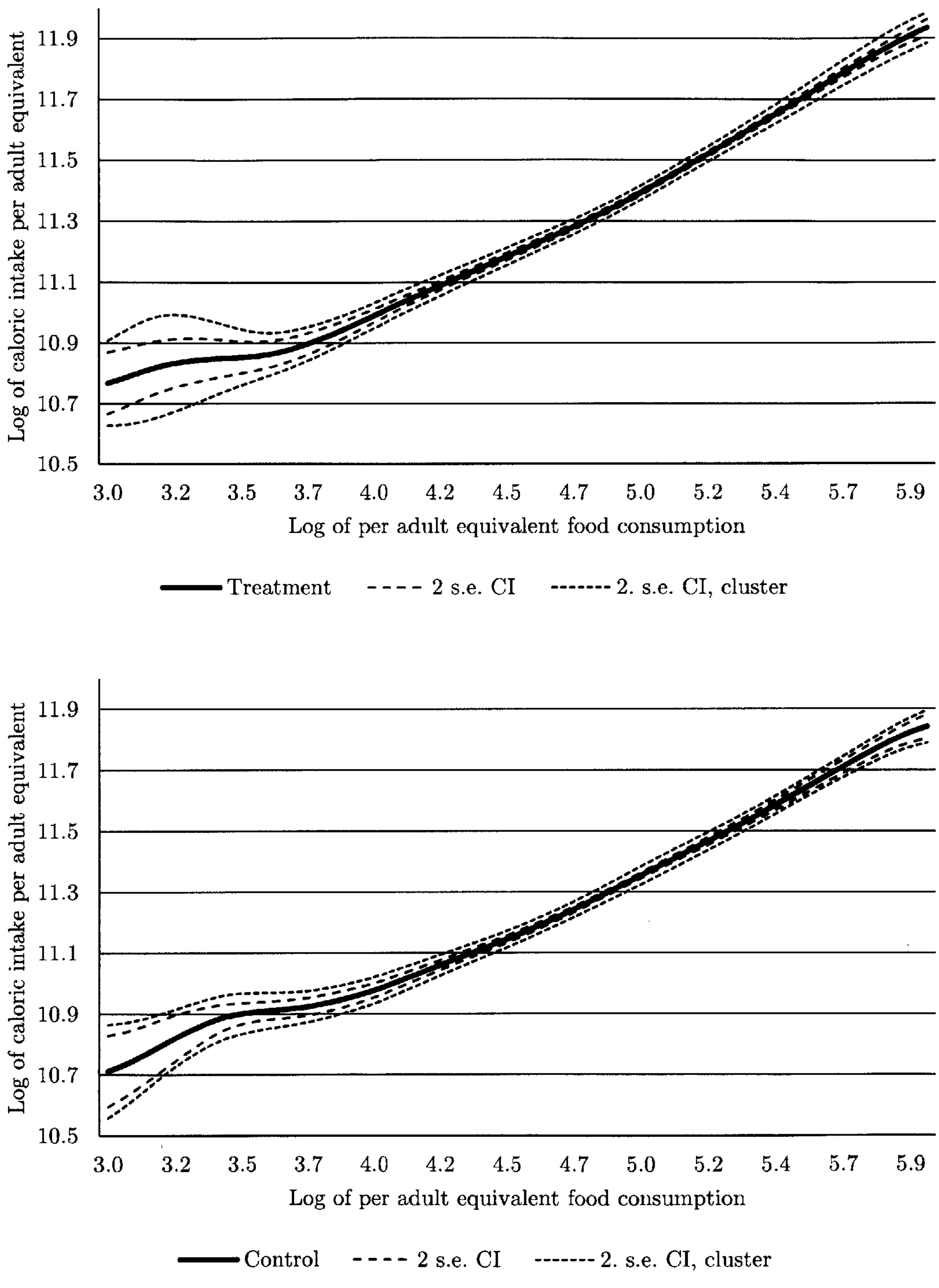


Figure 17. Calorie Engel curves, Progresa treatment and control groups

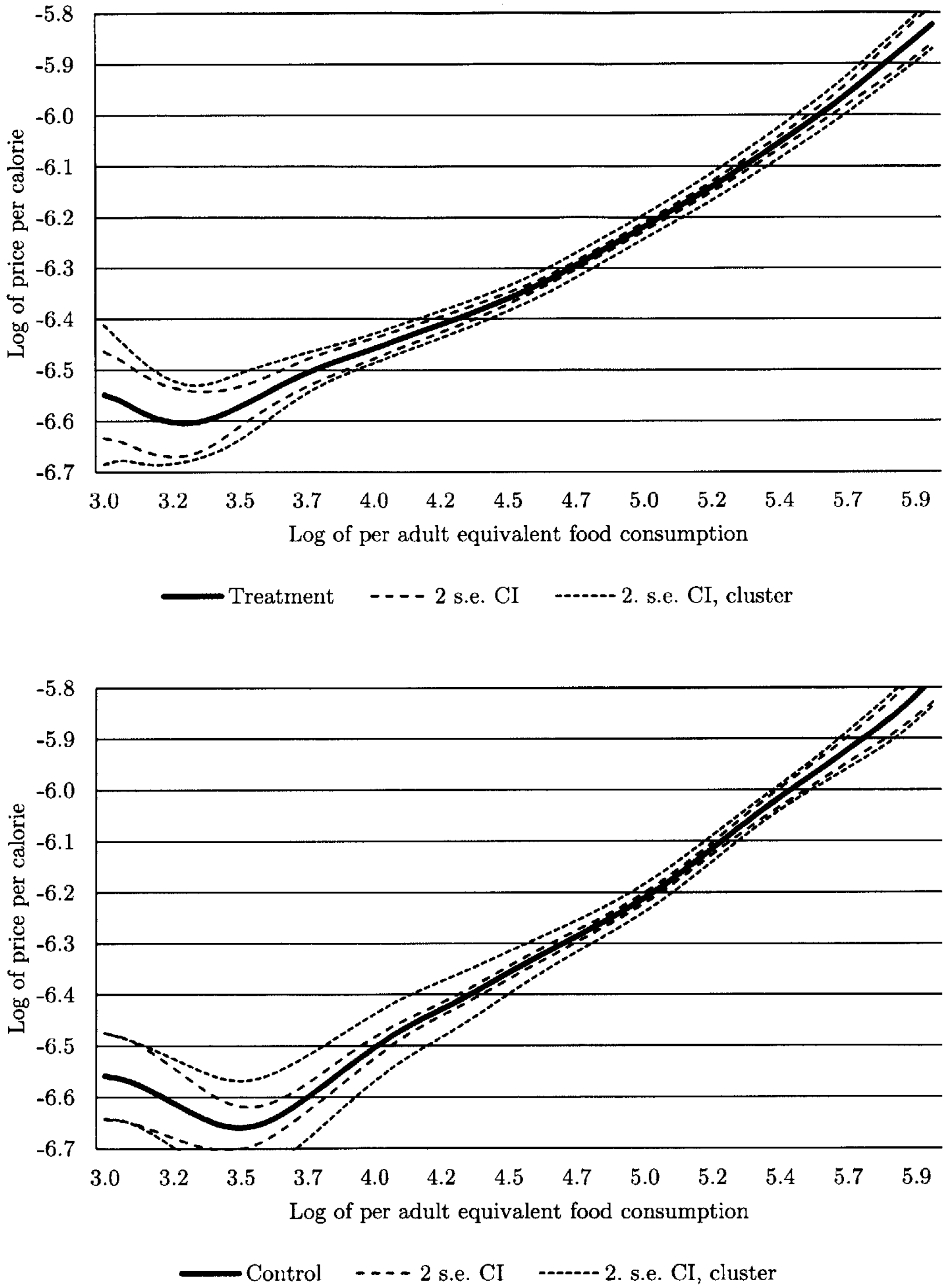
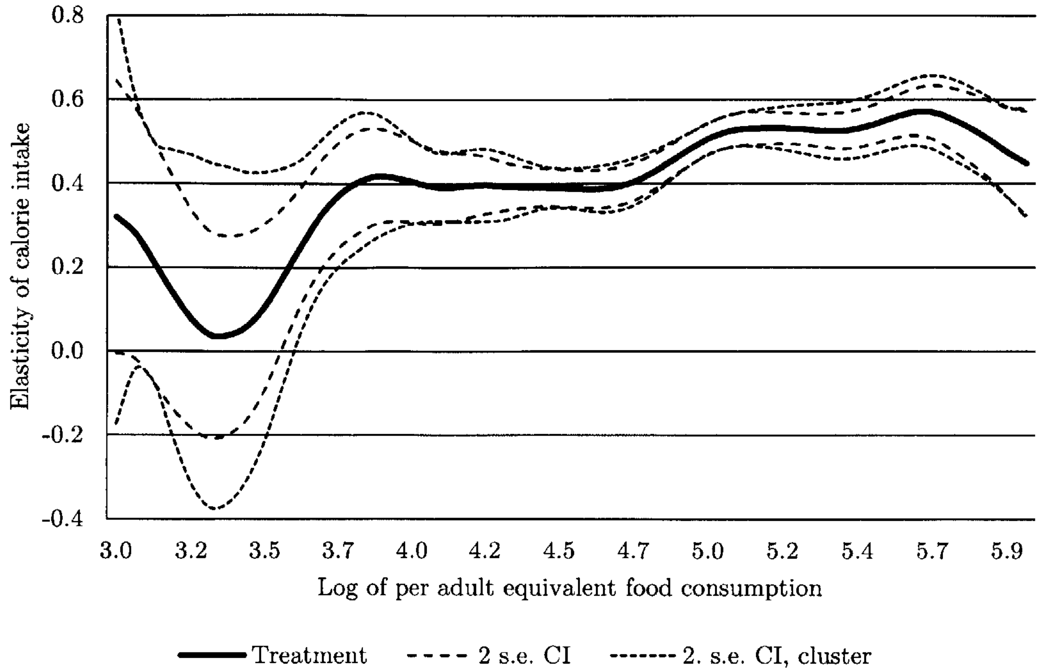


Figure 18. Cost per calorie at constant prices, Progresa treatment and control groups



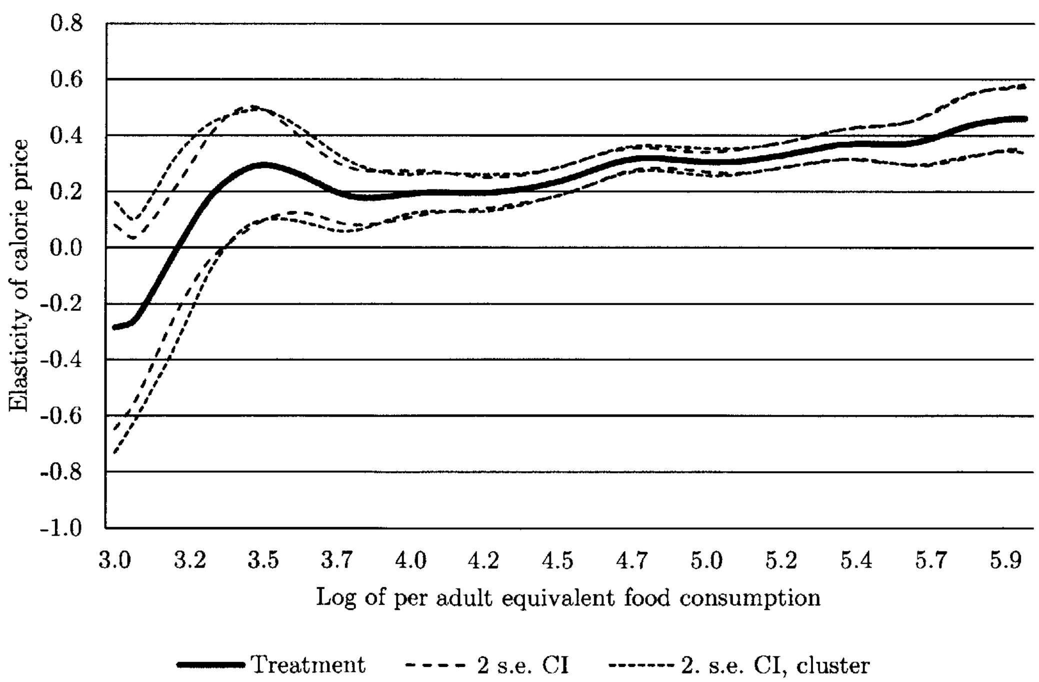


Figure 19. Elasticities of calorie intake and calorie price for program recipient households

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