# Children's Vulnerability to Weather Shocks: A Natural Disaster as a Natural Experiment *

**Javier E. Baez**
Maxwell School of Citizenship and Public Affairs
Syracuse University

**Indhira V. Santos**
Kennedy School of Government
Harvard University

April 2007

In October of 1998 Nicaragua was hit by Hurricane Mitch, one of the most powerful hurricanes of the Tropical Atlantic basin in the 20th century. We exploit the exogenous variation in the trajectory of the hurricane in a quasi-experimental design and show that large and aggregated shocks, such as natural disasters, have adverse medium-run effects on children's well-being, particularly in terms of health, nutrition and labor force participation. Conditional on being sick, children in affected areas were 30% less likely to be taken for medical consultation, even though there was no significant difference on the prevalence of illness between affected and non-affected children. Furthermore, the probability of being undernourished among children in regions hit by Mitch almost quadrupled (an 8.7 percentage point increase) and the overall distribution of their nutritional status significantly worsened as a result of the storm. On another margin, while we find no significant effect on school enrollment, labor force participation increased by 58% (an increase of 8.5 percentage points) among children in areas affected by the hurricane. Similarly, the proportion of children simultaneously enrolled in school and working more than doubled due to Mitch, going from 7.5% to 15.6%. Moreover, further evidence suggests that children were disproportionately affected by the shock as the nutritional status of mothers and adult consumption in affected areas were largely unchanged by the storm. This behavioral response has relevant implications for the nature of the resource allocation process in the household. Our results do not seem to be driven by a declining trend in investments in children prior to the shock, and are robust to different sub-samples and specifications, as well as to parametric and nonparametric estimation methods.

---

* The authors are graduate students in Economics and Public Policy, respectively. Special thanks go to Alberto Abadie, Farzana Afridi, Dan Black, Gary Engelhardt, Erica Field, Robert Jensen, Jeffrey Kubik, Jeffrey Liebman and Richard Zeckhauser for thoughtful comments to previous versions of this document. We also thank participants at the Development Lunch of the Economics Department (Harvard University), PREM Seminar (World Bank, D.C.), the Eleventh Annual Meeting of the Latin American and Caribbean Economic Association (LACEA, Mexico), the Third Annual Grad Student Conference on Latin American Studies (Cornell University), the Seminar on Latin American Studies, Moynihan Institute of the Maxwell School of Public Affairs, and the Workshop of the Economics Department (Syracuse University) and the CEDE Seminar (Los Andes University, Bogota). Any remaining errors are our own. The authors can be contacted at: jebaez@maxwell.syr.edu or Indhira_Santos@ksgphd.harvard.edu.

# 1. Introduction

Households in low-income countries face numerous risks –pests, diseases, droughts, floods– that not only cause significant fluctuations to their current income but can also reduce their middle and long-run earning ability by affecting their physical and human productive capacity. Moreover, a large proportion of these households depend heavily on agriculture, a highly volatile mode of subsistence. Insurance and credit markets in these countries are often incomplete, and many shocks are aggregate so that informal mechanisms for risk-sharing are not fully effective. Given this, adverse shocks have the potential of being very harmful for the welfare of poor households. Natural hazards add even more uncertainty to these already challenging environments and thus, weather-related events –the most common type of natural disaster– are particularly relevant for understanding the exposure of households' welfare to harmful shocks.

Since the 1980's, weather shocks not only occur more frequently but their impact has increased dramatically as well. In fact, between 1983 and 1993, natural disasters caused damage estimated at an average of US$67 billion per year, reflecting a 14-fold increase in the relative economic cost of these phenomena since the 1950s (Guha-Sapir, et.al, 2003). According to the International Red Cross (2005), nearly half of this increase occurred solely in the past two decades. Experts argue, in fact, that their frequency and cost are likely to further intensify due to global warming, environmental degradation and population growth. Moreover, these events are especially devastating for the poor, who often live in fragile dwellings and settle in risky locations such as river banks, flood plains, steep slopes and wild land without appropriate emergency systems.

The effects of weather shocks on daily life have captured the attention of analysts and policy makers all over the world in recent years, particularly after the tsunami in Asia in 2004 and Hurricane Katrina in the United States in 2005. In the literature on microeconomic development, more specifically, there has been a parallel interest in examining the consequences of adverse weather on households. This work, however, has mainly focused on testing the ability of households to smooth consumption (e.g. Deaton, 1992; Townsend, 1994; Grimard, 1997), rather than devoting attention to the welfare implications of these phenomena for individual members of the household in terms of particular outcomes. Investments in childhood education and health require large cash outflows and these expenditures may be difficult to make in the face of an income and asset shortfall. This may be particularly true for rural populations that lack formal markets for credit and insurance or, at best, have informal risk-bearing arrangements which do not fully protect consumption and fall apart in the presence of non-idiosyncratic events. If this is the case, a sufficiently large shock may take children out of school, push them into the labor market and worsen their health status. In the literature, Jacoby & Skoufias (1997) and Jensen (2000) have indeed found that income variability had an adverse effect on children's school enrollment and nutrition in settings with limited access to formal insurance.

In this paper, we investigate this hypothesis for a rarely studied natural hazard: a hurricane. Mitch, a tropical storm that attained hurricane status for three days and reached sustained winds of 180 miles per hour, hit Nicaragua in the last week of October of 1998. Hurricane Mitch is one of the most destructive storms ever to strike Central America, leaving behind more than 50 inches of rain and more than 20% of the population in need of new housing in Nicaragua alone. Approximately 45,000 households in 72 municipalities were directly affected, nearly 300 schools and dozens of health centers were left temporarily unusable, and one third of crops in the country was destroyed (World Bank, 2001). Because not all municipality segments in Nicaragua were directly hit by Mitch, we exploit this exogenous variation arising from the trajectory of the hurricane as a quasi-experimental design to estimate the medium-term effects of this shock on the school enrollment, labor supply and health status of children in affected areas. To do so, we implement a double difference analysis (DID) and construct our experimental groups using panel data from the Living Standards Measurement Study (LSMS), a household-level survey collected in 1998, 1999 and 2001 by the World Bank and the National Institute of Statistics of Nicaragua (INEC). Thus, our treatment group is comprised of children in portions of municipalities (segments) affected by Mitch, as defined by the 1999 LSMS and discussed below in more detail.

Our results indicate that large and aggregate shocks, such as natural disasters, have adverse medium-run effects on children's well-being, particularly in terms of health, nutrition and labor force participation. Conditional on being sick, children in affected areas were 30% less likely to be taken for medical consultation, even though there was no significant difference on the prevalence of illness between affected and non-affected children. Furthermore, the probability of being undernourished among children in regions hit by Mitch almost quadrupled (an 8.7 percentage point increase) and the overall distribution of their nutritional status –especially of those in the lower tail– significantly worsened as a result of the storm. On another margin, while we find no significant effect on school enrollment, labor force participation increased by 58% (an increase of 8.5 percentage points) among children in areas affected by the hurricane. Similarly, the proportion of children simultaneously enrolled in school and working more than doubled as a result of Mitch, going from 7.5% to 15.6%. Moreover, further evidence suggests that children were disproportionately affected by the shock as the nutritional status of mothers and adult consumption in affected areas were largely unchanged by the storm. Based on placebo experiment estimates, our results do not seem to be driven by a declining trend in investments in children prior to the shock. The main findings are also robust to different sub-samples and specifications, as well as to parametric and nonparametric estimation methods.

The rest of the paper is organized as follows. First, in the background section, we review the existing evidence on the consequences of shocks for children's well-being, discuss a simple conceptual model to help frame the effects of a hurricane on children in a setting of imperfect markets and describe the trajectory of Hurricane Mitch and its effects in Nicaragua. Section 3 describes the data, while Section 4 presents our empirical strategy, including the identification design, main findings and some robustness checks to our strategy. Section 5 offers a brief discussion on the theoretical implications of our findings. Finally, Section 6 concludes.

## 2. Background

### 2.1 Previous Findings

In order for households to achieve their optimal consumption path, it is necessary for them to smooth consumption across time and states of nature. However, the literature on this topic has long revealed evidence of imperfect smoothing in developing countries where relevant market failures are more likely. For instance, Paxson (1992) tested the idea of perfect smoothing in Thai villages using cross-sectional data on income and expenditures of farm households together with rainfall information. Although her estimates of the marginal propensities to save out of transitory shocks are quite high (between 0.73 and 0.83), they are not supportive of full insurance. Deaton (1992), using data from Côte d'Ivoire, found that fluctuations in household income were only weakly associated with community shocks where the risk is assumed to be shared. Along the same lines, Townsend (1994) examined the performance of all the institutions –formal and informal– that can jointly insure rural households at the village level using longitudinal data from India. His findings indicate that transitory idiosyncratic events were highly smoothed away but still far from the first best with fully functioning markets for credit and insurance.

Other results in the literature go in the same direction.[1] That is, consumption partially tracks income in low-income countries, and particularly in rural populations. Natural disasters, rather aggregate shocks, make it even harder to isolate consumption from income paths. Santos (2006) found that inter-household transfers increased in Nicaragua in the aftermath of Mitch but, for the median household, new transfers only offset 15% of the losses arising from the event in the eight months after the storm. The analysis suggests that formal credit markets were largely absent in Nicaragua and that households were not able to fully share the risks arising from the storm through other channels.

If households cannot perfectly smooth consumption, then they are forced to finance a fraction of their current consumption and investment out of today's income. As a result, households could be forced to reduce the resources directed to basic expenditures such as those allocated towards the education and health of children, especially considering that significant liquidity is needed to cover this type of expenses.[2] Even though these mechanisms of adjustment could be evident, the existing literature on the effects of large adverse shocks on children is surprisingly limited. Still, the available evidence suggests that negative shocks tend to be associated with a decrease in children's investment in terms of education and health.

Economic crises, in particular, have been found to be associated with a significant deterioration of social indicators at the macro level. During Argentina's economic downturn in 1995, for instance,

---

[1] See Murdoch (2003) for India and some estimates for Latin America like those of Garcia-Verdú (2001) for Mexico and Barrera and Perez (2005) for Colombia and Nicaragua.

[2] In Nicaragua, costs associated with children's education and health can represent an important share of a household's budget. For instance, in 1998, the median household expenditures for sending children to school (tuition, transport, enrollment fees, uniforms, books and other school supplies) was $2,250 córdobas (US$215) per year – half of their median household income per capita (data from 1998 LSMS).

per capita daily protein intake fell 3.8% while growth in gross primary enrollment declined from 2.2% in 1993 to 0.8% in 1996. For the same year, mortality from anemia increased from 6.3 deaths per 100,000 live births in 1993 to 7.9 in 1995 among children under the age of 1 at the time of the crisis in Mexico. Similarly, after the 1997 crisis in Indonesia, nutrition worsened for children under the age of three, while for the poorest quartile of the population the share of children ages 7-12 not enrolled in school rose from 4.9% in 1997 to 10.7% in 1998 (World Development Report, 2001c). Although the worsening of children's socioeconomic status may not be explained entirely by responses to the crisis at the household level, they can hardly be solely attributed to macro effects.

Like economic crises, natural disasters can extensively affect the educational and health status of the population afflicted, particularly children. Foster (1995) showed that floods in Bangladesh were associated with lower child weight, especially in households that were credit constrained. After the floods, 46.2% of the landowning households and 64% of the landless households took out loans. Children in the latter families were in worse health conditions since they had access to relatively more expensive credit. Jacoby & Skoufias (1997) tested a structural dynamic model of human capital accumulation and insurance behavior against Indian data from 10 villages with different climatic characteristics. They showed that children were less likely to enroll in school in periods of negative income shocks and argued that this insurance strategy had pervasive consequences in the long-run, especially for small–farm households which had a greater probability of taking children out of school after unanticipated shocks. Similar responses have also been identified in rural areas of Africa. Jensen (2000) exploited inter-regional weather variation between 1985 and 1988 and cross-sectional data from Cote d'Ivoire to find that deviations from the historical mean were associated with an average decrease in school enrollment of 20%. In addition, the probability of being taken for medical consultation if ill and the nutritional condition of children in affected areas worsened significantly. Likewise, Beegle, Dehejia and Gatti (2003) used panel data from Tanzania between 1991 and 1994 and found evidence that temporary shocks increased the prevalence of child labor, especially in households with less collateralizable assets.

This paper contributes to the literature in several ways. First, it adds to the analyses of the effects of large adverse shocks on the well-being of children, for which the existing evidence is limited. To the best of our knowledge, this paper is the first attempt to examine these issues in the presence of a natural disaster which combines both the strong winds and torrential rains. Rarely has there been an opportunity to study such a large and exogenous event such as Hurricane Mitch. Second, we explore the effects of the hurricane three years after the episode. The persistence of adverse effects on children hints at important long-run consequences of shocks, especially if we take into account that education and health are important determinants of future earnings and welfare. Theoretically, this paper has significant implications for the literature on household decision-making since our findings suggest that children are not only worse off after a natural disaster, but that they are disproportionately affected by these events. More generally, our work contributes to the understanding of natural disasters. This constitutes valuable information for policy makers, as well as national and international non-governmental organizations, interested in designing comprehensive policies to deal with large negative shocks.

## 2.2 Conceptual Framework

As evidenced from the damages reported by households in the aftermath of the storm, something we will return to in more detail later, natural disasters can adversely affect not only the income of the household but also its assets and the physical well-being of its members. In addition, they can have a negative effect on a country's infrastructure and overall macroeconomic environment. More formally, we follow Skoufias (2001) and develop a simple single-period model of household decision-making with full information and a unitary household that stresses the mechanisms through which a hurricane can potentially affect children's outcomes. [3] We leave the main details of this model for Appendix 1 but briefly discuss its implications in this section.

The medium-term effects of a hurricane on the household's investment in children operate through three different channels. First we consider what we call direct effects, which include the disruption of school and health services and damage to complementary infrastructure, as well as the loss of assets and inventories and the death or illness of family members. Second, there are indirect effects, which reflect the change in the income of the household. One the one hand, income can

[3] Regarding the unitary household assumption, in this study we use panel data for a group of households affected by Mitch and for others not affected by the Hurricane; therefore, by using a unitary model, the assumption is that the balance of power in the household did not change in a differentiated manner for the two specified groups. This seems to be a realistic assumption and, thus, we consider the unitary model appropriate for our purposes.

decrease due to the loss of crops, jobs or business; on the other, the number of jobs and, thus, income can rise as a result of reconstruction initiatives and possibly higher levels of public investment. Finally, we call secondary effects those related to the slowdown in the economy in general as a result of inflation, increased debt, fall in production, etc.

Each of these effects has different implications for the optimal allocation decision of the household. In our model, disturbances to educational and health services, as well as the loss of complementary infrastructure and households assets (i.e. direct effects), ceteris paribus, lead to families investing less in children's schooling and health. The interruption or destruction of relevant services, including damage to physical facilities and lack of required personnel and supplies, increases the marginal cost of the goods and services associated with accumulating human capital, while a decrease in household assets constitutes a decrease in the household's permanent income. Similarly, the incapacity of a productive parent, the loss of crops, jobs or business lead to a fall in income that –in an environment of incomplete capital markets– can further tighten the household's budget constraint. As noted above, this drop in income can be partially or entirely offset by an increase in employment due to rebuilding activities.

Finally, the slowdown of the economy is expected to decrease the demand for labor and wages. This decrease in wages may be reinforced by an increase in labor supply as households try to cope with the effects of the shock. There is an income and a substitution effect associated with this change in wages. On the one hand, the latter would predict an increase in children's human capital since the opportunity cost of human capital, the wage, is now lower. However, as the income effect goes in the opposite direction, formally, the net change would be unknown. On the whole, as described by the model, the theoretical effects of a shock like a hurricane on the investment in children's human capital are ambiguous. The end result is, hence, an empirical matter.

### 2.3 Hurricane Mitch in Nicaragua

Nicaragua is, after Haiti, the poorest country in the Western Hemisphere. According to the last population census in 1995, the country is divided in three main geo-political regions: Pacific, Central and Atlantic. The highest concentration of poverty is found in the two semi-autonomous regions of the Atlantic, while the lowest is found in the capital city (Managua) and the rest of the Pacific region (World Bank, 2001b). Nicaragua is further divided into departments (15) and two autonomous sub-regions which are, in turn, divided into municipalities (147). When Hurricane Mitch hit the country in October 1998, Nicaragua had a GDP per capita of US$741 (constant 2000 US dollars), 44.71% of the population was living with under US$1 a day, 79.03% with under US$2 a day, and 24% of individuals aged 15 and above were illiterate. Moreover, in 1998, net enrollment in primary school was at 74% and 12.8% of children aged 10-14 were working, although this proportion has decreased to around 8% in recent years. In terms of health, child malnutrition is remarkably high as one quarter of children under five was undernourished in 1998 (World Development Indicators, 2007).

Among the Latin American and Caribbean countries –with the exception of the island of Montserrat, Nicaragua was the hardest hit by natural disasters between 1970 and 1999, with cumulative losses estimated at 338.4% of 1997 GDP (Charvériat, 2000). During the last two decades, the country has been affected by earthquakes (1992), droughts (1994, 1997, 2001), wild fires (1991), floods (1990, 1998) and wind storms (1993, 1998). Of all of these natural disasters, Hurricane Mitch was the strongest in terms of the number of people affected and damage costs. Mitch started as an ordinary tropical depression, but on October 24 it was classified as a hurricane, reaching winds of up to 90 miles per hour and 180 miles per hour two days later. The storm changed course several times; Cuba and Jamaica, at first, and Mexico and Belize, next, were alerted. On October 27, Mitch unexpectedly moved inland in Honduras and steadily weakened, but still its torrential rains brought in five days more precipitations than the average rainfall of a full year. Following, Northern and Pacific Nicaragua received the heaviest rains –over fifty inches of rain in five days, before the storm lost strength as it passed through Guatemala and El Salvador (McKinley & Stevens, 1998).

The hurricane struck Nicaragua from October 27 to October 31, 1998 and mostly hit the Central and Pacific regions of the country.[4] Around 19 percent of the population (870,000 people) was affected (INEC, 1999). The strong winds and the historic amounts of rain that accompanied Hurricane Mitch, compounded by the usually weak housing structure in Nicaragua, generated extensive structural damage. Approximately, 45% of households surveyed in the 1999 LSMS reported their dwellings having being harmed during the hurricane and, in fact, 29.4% had to

[4] See Appendix 2 for maps that describe the trajectory of the hurricane in detail.

temporarily leave their home. Furthermore, 17.3% of the affected households declared having permanently moved to another residence due to Mitch, and 23.5% rebuilt or repaired their house after the disaster. However, most families that abandoned their home temporarily or indefinitely did not move very far away from their pre-shock location. On average, they settled roughly 2.5 miles away from their damaged dwellings. Table 1 includes a summary of the immediate effects of the storm as reported by the victims.

Rural areas were particularly hit, representing 77.4% of all affected households in the survey. In 56.7% of the affected households at least one member was working on his own land when Mitch hit, and 83.5% of these families recognized Hurricane Mitch as the main factor affecting their agricultural activity in the 12 months prior to the survey.[5] The torrential rain that accompanied Mitch destroyed a large part of the basic grains, one-third of the 1998-99 banana harvest, as well as export crops such as sugar cane. This destruction had devastating consequences in a country where, in 1998, 36 percent of the economically active population was employed in agriculture and where this sector represented roughly 28 percent of the country's GDP (ECLAC, 1999). In the 1999 LSMS, households were asked about the losses experienced in agriculture due to the storm: 96.6% of the households reported having lost crops, 10.4% reported having lost productive animals, while 9.2% suffered losses related to their agricultural property. Due to Mitch, according to the 1999 LSMS survey, the average real agricultural losses per household were $2,933 córdobas (US$277)[6], representing more than 115 percent of households' average monthly income in 1998. Table 2 summarizes the information related to agricultural losses.

In terms of local infrastructure, although 1500 miles of roads and a number of bridges were reportedly partially destroyed, 22 percent of households in the affected areas considered that access to roads had improved from a year earlier –indicating a significant reconstruction effort (1999 LSMS). However, as is discussed below, we are particularly concerned with the effect of Mitch on the supply of schooling and health services since it can be a confounding factor when trying to identify the impact of the storm on schooling and health demand indicators that is the objective of this study. It is estimated that more than 300 schools throughout Nicaragua were affected (World

---

[5] The other options included: drought, pest, inundations, robbery, extortion, physical violence, land invasion, kidnapping, fires, or "other".

[6] US$1= 10.58, 11.81 and 13.37 *córdobas* in 1998, 1999 and 2001, respectively.

Bank, 2001). Nevertheless, disruptions to schooling services –at least in our sample– seem to have been few and brief. In the areas surveyed in 1999, no family cited the school being destroyed by Mitch as a reason not to enroll a child in classes, and average travel times to school were also largely unchanged after the storm. Other supply indicators, including the presence of teachers and child space, seem to have actually improved by 1999 and 2001.[7] In addition, the impact of Mitch on schooling may have been limited by the fact that when the storm hit Nicaragua in November there was only one more month left of the school year. The academic year was then cut short and the start of the new one was pushed back approximately a month, giving more time to rebuild schools and reorganize students (Ureta, 2005). Similarly, disruptions in health services seem to have been larger immediately after the storm, but significantly less severe by 2001. In the 1999 LSMS, only 0.3% of individuals that were ill in the week prior to the survey and did not went for consultation attributed this to the health center having been destroyed by the storm and 0.85% to the lack of appropriate personnel. The corresponding proportions in 2001 are also negligible.

In general, it is estimated that Hurricane Mitch generated in Nicaragua losses greater than $1 billion or 51 percent of the country's 1997 GDP (Guha-Sapir et.al, 2003). To offset these losses, there was a large influx of emergency relief aid in the aftermath of the storm. Bilateral emergency assistance for Nicaragua from OECD countries alone was $34.8 million in 1998, $105.7 million in 1999 and $17.1 million the following year (OECD, 2004). However, while monetary and in-kind donations, such as food, housing, construction materials, clothing, and medicines were widespread, much of the promised aid aimed at the reconstruction process was not delivered, and today many roads and bridges are still down and housing projects left incomplete (Hiscock, 2005). Moreover, previous work has found evidence that aid, although well directed to affected municipalities, was not well-targeted towards the most vulnerable households within those communities (Ambler, 2005; Lazo, 2005). Most households in the 1999 survey benefited from food and health programs (45.3% and 38.1%), followed by donations of clothing and employment programs (Table 1). While in 1998 only 0.4% of all households received any non-private donations, in 1999 52% of the affected families were benefited by this sort of transfer. The average size of the donations per household went from $1.08 ($11.37 *córdobas*) in 1998 to $40.83 ($482.30 *córdobas*) in 1999.

---

[7] The proportion of households affected by Mitch reporting these supply-side reasons as justifications for not enrolling their children in school decreased gradually between 1998 and 2001: going from 4% in 1998 to 1.3% in 1999 and 1% in 2001.

# 3. Data

For our main analysis, we use data from the Nicaraguan Living Standards Measurement Studies (LSMS) carried out by the National Institute of Statistics (INEC) in 1998, 1999 and 2001, with the support of the World Bank.[8] The LSMS are very rich panel surveys with multistage stratified samples that gather information on a wide range of topics, including income, expenditure, education, and health at the household and individual levels. In 1999, in the aftermath of the hurricane, it was decided to do a follow up of the 1998 survey in affected areas in order to assess the effects of Mitch. By November 1998, personnel from LSMS visited the country to identify the affected areas. Months later, interviewers went back to households that met two conditions: 1) they were located in segments of municipalities[9] affected by the hurricane as determined previously in the November visits and 2) surveyed in the 1998 round. Hence, we identify a household as being directly affected by Mitch in the 1998 and 2001 surveys if it was located in a municipality segment visited in the 1999 LSMS round.[10] The availability of panel data provides, therefore, a unique opportunity to study the impact of a natural disaster on household welfare.

In addition to the LSMS, in Section 5 we use cross-sectional data from the 1998 and 2001 Nicaraguan Demographic Health Surveys (DHS) in order to further explore other behavioral responses and their implications for the process of resource allocation within the household. The DHS are nationally representative household surveys, using in Nicaragua the same sample framework as the LSMS, and provide a large range of data in terms of household characteristics and individuals' health and nutrition information.[11]

Our initial working sample is comprised of 2,764 households, of which 396 were affected by Hurricane Mitch and are part of the treatment group, with the remaining representing the

---

[8] See INEC, (2000), "Comparative Indicators in Zones Affected by Hurricane Mitch, according to Household Surveys" for a detailed explanation of the methodology followed in the LSMS. Field work for the EMNV98 was carried out between April and August 1998; for the EMNV99, in May and June 1999; finally, for EMNV2001, interviews were carried out between June and August of 2001.All monetary values are expressed in 1998 córdobas.

[9] The LSMS data in Nicaragua was divided in census segments, consisting of a maximum of 50-60 dwellings.

[10] The interviewers followed all households that in 1998 had been located in areas that were later affected by Mitch - even when they moved out of the municipality- as long as they stayed in the same region as in 1998. Only 2.25% of the households visited in 1999 had permanently moved to another region after the Hurricane. Although the 1998 and 2001 surveys are representative of the whole Nicaraguan population, the 1999 follow-up is not representative of the total population in Nicaragua affected by Mitch (INEC, 2000).

[11] For more information on the methodology of the DHS surveys, please see http://www.measuredhs.com/.

comparison group. The data covers 15 departments and 2 autonomous regions in 126 surveyed municipalities. Table 3 presents selected pre-shock mean characteristics for our total sample, as well as for a sub-sample of rural households. Both samples are restricted to households with at least one child and that were part of both the 1998 and 2001 surveys.

Households in the sample are largely poor (median annual income per capita of US$296), with low levels of education (average of 4.1 years of education for head of households) and large families (average family size of 6.1 members). Households living in areas affected by the adverse shock were more rural and had lower average income per capita ($3,382 córdobas or US$281.80) than other households ($6,279 córdobas or US$523.25).[12] There are other differences in terms of educational attainment of the parents, the proportion of households headed by women, owning a dwelling and the distance to health centers and primary schools. These differences are overall explained by a higher degree of rurality in the areas affected by the hurricane, and most either disappear or become very small as we condition on location (right panel of Table 3). In terms of income per capita, even though the differences in means persist, there is no significant discrepancy in medians. That is, once we include geographic controls, households spared by Mitch are fundamentally similar to those affected by the storm and, as a result, constitute a good control group for our study on the basis of relevant observable characteristics.

# 4. Empirical Strategy and Findings

## 4.1 Identification

As noted before, the objective of this paper is to examine whether children living in areas directly affected by Hurricane Mitch experienced lower investments in health and nutrition, lower enrollment rates in school, and worked more due to the shock. Ideally, we would like to calculate the effect of the storm on each of these measures of children's well-being by comparing the actual outcome of the affected child with what that outcome would have been in the absence of the shock.

[12] Our measure of household income results from the addition of in kind and cash earnings from all jobs, net income from agricultural activities and the non-agricultural family-owned business, the value of all goods and services from agricultural activities and own business that were consumed by the household and all other sources of income (rents, pensions, private and public transfers, etc.).

Obviously, it is impossible to observe the same child in these two scenarios and thus, we rely on the construction of a proper counterfactual to assess the impact of the hurricane. Since Mitch's trajectory was exogenous and it did not directly affect all areas in Nicaragua, households in regions spared by the storm constitute a natural control group. Hence, our approach is to compare the changes in schooling, child labor, health and nutritional outcomes experienced between 1998 and 2001 among children in regions directly hit by Mitch to those that occurred among children in the control areas.

To illustrate our research design more formally, we follow Angrist and Krueger (1998) and set $C_{it}$ to represent a particular outcome of a child type $i$, where $i$ = 1 if the child is in a municipality segment (i.e. sample district) affected by Mitch and $i$ = 0, otherwise. Let $t$ represent the year, with $t$ = 1998 (pre-shock) or $t$ = 2001 (after-shock). There are two possible states of the world $s$: $s$ = 1 with Mitch, and $s$ = 0 without the shock. The conditional mean function for child outcomes is:

$$\mathrm{E}\left[C_{0rt} \middle| \; i,s,t\right] \text{ if the child is not affected by Mitch; and} \tag{1}$$

$$\mathrm{E}\left[C_{1rt} \middle| \; i,s,t\right] \text{ if the child is affected.} \tag{2}$$

However, as mentioned above, for t = 2001 we only observe (2) when $s$ = 1. Then, we use similar villages that were not affected by Mitch to estimate this counterfactual:

$$\mathrm{E}\left[C_{0rt} \middle| \; i=0, s=1, t=2001\right] \tag{3}$$

In the absence of the shock, assume that children's outcomes can be written in the following simplifying manner:

$$\mathrm{E}\left[C_{i0t} \middle| i, r=0, t\right] = \alpha + X\beta \tag{4}$$

Further, let's assume that the effect of the shock ($M$) can be captured by a constant $(\delta)$ – namely homogenous treatment effects. For instance, any outcome of child $i$ in any region can be described as follows:

$$C_i = \alpha + \delta M_i + X\beta \tag{5}$$

Under these conditions, and further assuming that the outcome variables for households had the hurricane not taken place, would have had the same growth rate as those of the comparison group, the average causal effect of the shock among affected segments is identified by the double difference estimator:

$$\delta = \{E[C_{1,2001} | i = 1, t = 2001] - E[C_{1,1998} | i = 1, t = 1998] -$$
$$\{E[C_{0,2001} | i = 0, t = 2001] - E[C_{0,1998} | i = 0, t = 1998] \quad (6)$$

As in Jensen (2000), we are interested in measuring resource flows related to children's outcomes in education, child labor and health. For education, our main indicator is school enrollment, while for child labor force participation we look at the probability of a child being either working or looking for a job.[13] For health, we examine the utilization of medical services, conditional on being sick and then explore some potential effects on nutritional status by analyzing the weight-for-height measure.[14]

In order to instrument for the shock, we construct a dichotomous indicator equal to one if the household was located in 1998 in a municipality segment affected by Mitch (as indicated by having being surveyed in 1999) and zero otherwise. This dummy variable allows us to identify the average effect of the shock among the experimental group.

Our research design allows us to identify only lower-bound-estimates of the impact of Hurricane Mitch on children's outcomes for various reasons. First, a natural disaster, as an aggregate shock, is also expected to have an indirect negative impact on households in municipality segments not physically hit by the storm –as described in Section 2.3. Households living in control regions were also exposed to the macro effects of the disaster and perhaps experienced a lower level of transfers as public financial and physical resources may have been diverted towards regions in more need of aid. Second, migrants from treated areas –which we do not observe in the second round– may be the ones most heavily hit by the hurricane and, thus, we observe only the remaining part of the distribution[15]. Third, although long-distance migration does not seem to be a major issue in our

---

[13] The definition used here to classify children as participating in the labor market includes those who were either working for at least one hour (counting also labor in family businesses) or looking for a job during the week before the survey.

[14] We use the weight-for-height Z score in reference to the NCHS median recommended by the World Health Organization. As discussed in Jensen (2000), this measure reflects the short-term or current nutritional status of the child (health investment flow), as opposed to the height-for-age indicator which is more related to long-term nutritional conditions (health stock) of the child.

[15] As discuses further in the section on robustness checks, there is a possibility that migration can lead to an upward bias if households that leave are the least credit constrained. However, we find no evidence for this.

sample, migrants that moved to unaffected regions may have overcrowded the already scarce social services in these areas as well. Fourth – and discussed further in section 4.3, public aid after the shocks could have gone to the areas most affected making treatments better off than what they would have been in the absence of the aid. As a consequence, our models may produce smaller estimates than the actual effects as the DID approach is comparing affected households with others that are also worse off due to the treatment. Given the consistent sign of these potential sources of bias, our results are still very informative about the changes in children's welfare.

## 4.2 Results

In this section we discuss our results for the impact of Hurricane Mitch on children.[16] We assess children's well-being in terms of differential changes (between 1998 and 2001) in three main subjects: (a) schooling and labor force participation, (b) disease prevalence and health care utilization (conditional on being ill) and, (c) nutritional status. We focus on children aged 6-15 for education and labor supply, 0-15 for health measures and 0-4 for nutritional status. Initially, we estimate simple DID models for each of the outcomes of interest. If Hurricane Mitch had an effect on children's enrollment, labor force participation, health and nutrition, then it should be reflected in the raw data. Results are summarized in Table 4. There are no significant pre-shock differences between rural households located in affected areas and those not directly hurt by Mitch in terms of any of our outcome variables.

Before Mitch, 69.3% of children in rural affected areas were enrolled in school, and while enrollment rates increased markedly for both the treatment and the control group between 1998 and 2001, this rise is proportionally larger among affected children. The enrollment rate increased by 5.9 percentage points more in the treatment group than in the control group (8.5% of the initial rate). This finding reflects the documented efforts in increasing school enrollment during these years in

[16] We focus on rural households, although results for the whole sample are also included in the output tables. Rural households in the control and experimental groups are more similar in terms of pre-shock characteristics, especially in relation to the outcomes analyzed here. As for the total sample, the observed differences in 1998 in the outcomes of interest between the treatment and the control groups (Table 4) are not necessarily problematic since they seem to arise from observed factors (especially location) which are taken care of by the DID estimation method.

rural areas in Nicaragua[17]. We get back to this issue later in the paper when we show that this difference disappears once we condition on initial characteristics of the individual and the household, as well as for municipality fixed effects and pre-shock local public programs.

Table 4 also reports simple DID estimates for the effects of the shock on the likelihood of a child joining the labor market (either working or looking for a job). Before Mitch, 18.5% of rural children in both the control and the treatment groups participated in the job market. And while labor force participation decreased between 1998 and 2001 in non-affected areas, it increased markedly in treatment areas. The estimates suggest that Mitch was associated with an increase of 5.6 percentage points (almost one third of the original rate) in the proportion of children in the job market in areas hit by the storm.

In fact, when we look at the proportion of children both enrolled in school and in the labor market, the results confirm the two previous findings. Even though prior to Mitch 8.5 percent of children in affected and non-affected rural areas were jointly attending school and participating in the labor market, the shock generated an increase of 6.1 percentage points more in this fraction among the former –an increase of 71%. If this result reflects relatively low substitutability between school and work, then the observed increase in labor force participation in affected areas would come at the expense of children's leisure time.[18]

The next set of results in Table 4 includes two health dimensions: the prevalence of illness and utilization of medical services (conditional on being sick). For the two age groups considered, results are similar and quite large. On the one hand, we find no statistical difference – between control and treatment groups - in the proportion of children sick before the shock, and Mitch does not seem to have affected systematically differently the two groups along this measure. However, children in affected rural areas were significantly less likely to visit the doctor after the hurricane. Conditional on being ill, simple DID estimates indicate that children between 0-6 years old in the experimental sample were about 55% less likely to be taken for consultation after Mitch (starting from a pre-shock

---

[17] During the 1990's important progress was made in the education sector in Nicaragua in terms of primary and secondary education coverage. The net enrollment rate in primary school went from 76% in 1998 to 83% in 2002, while secondary school enrollment went from 33% to 38% (WDI, 2007).

[18] This result is consistent with existing evidence that suggests that child labor in Latin America does not necessarily imply that the child stops going to school (Carranza, 2005). However, information on the number of hours dedicated to each activity would be needed in order to be conclusive on this issue.

rate of 52.8%). For children between 6-15 years of age, the effect was also large since they were 40% less likely to use health services after Mitch conditional on being ill (starting from a pre-shock rate of 24%).

In terms of nourishment, results are similar to the ones obtained for labor and health care use, namely Hurricane Mitch had a large and negative effect on children's nutritional status. As explained before, we use the child's weight-for-height (WFH) Z score, a summary measure of current nutrition. Estimates for the effect of Hurricane Mitch on nutrition are obtained for children between 0 and 4 years of age since we have no anthropometric information for older members of the household. More specifically, we analyze two related indicators: the Z-score itself and the probability of children being severely undernourished, i.e. more than two standard deviations below the reference median.

Figure 1 shows Z score WFH kernel densities for the whole sample of children before and after the shock, as well as separated by gender. This exercise is useful because it allows us to understand the effects of Mitch on the distribution of nutritional status, in addition to the probability of being malnourished. The nutritional distribution of children in the treatment and control groups is rather similar in the pre-shock period, while a significant relative worsening among affected children is evident by 2001. The graphs show that there was a large change in the shape of the distribution among children affected by Mitch, in particular among those already below the reference median (the distribution became much bulkier on the left hand side). These children belong to households that are slightly poorer, have more members and their parents are less educated. Although results are quite similar for boys and girls, the former seem to be relatively worse off in terms of the impact of the shock, contrary to what is often found in studies based in South Asia (Filmer, et,al, 1998; and Behrman, 1988). The statistical analysis confirms the graphical description. Hurricane Mitch significantly worsened the nutritional status of children –as measured by the WFH indicator– in treated areas. In particular, children in affected regions experienced a surplus increase of 7.6 percentage points in the probability of being severely malnourished in comparison to those in the control group. That is, while in 1998 4.2% of the children aged 0-4 in the treatment areas were severely undernourished, three years later they became almost twice more likely to be undernourished due to Mitch (Table 4).

Our simple DID analysis so far has shown that Hurricane Mitch had a large and negative effect on treated children by significantly increasing their labor force participation, decreasing the probability of being taken for consultation if ill and worsening their nutritional status. However, one may think that the control and the treatment groups are different across some key characteristics, as discussed in reference to Table 3. Therefore, one needs to condition on those variables to pick up the true causal effect of the shock and increase the precision of the estimates by reducing the unexplained variance from the raw DID models. The general form of the base regression equation for these extended models is the following:

$$C_{itd} = \alpha + \varphi_i + \beta_1 X_{itd} + \beta_2 \tau_t + \beta_2 Treat_d + \beta_3(\tau_t \ x \ Treat_d) + \beta_4(\tau_t \ x \ Treat_d \ x \ Z_{itd}) \qquad (6)$$

where *i* indexes individuals, *t* indexes years (1 if after 1998, 0 otherwise) and *d* indexes the treatment and control groups (1 if hit by the hurricane, 0 otherwise). *C* represents any of our outcome variables associated with children's well-being (e.g. whether child is attending school), $\phi_i$ is a household fixed effect, *X* is a vector of both household demographics and pre-shock observable characteristics at the household and municipality level, $\tau$ is a fixed year effect and *Treat* is a dummy for treatment group (1 if treated, 0 if control). The interaction associated with $\beta_3$, the main coefficient of interest in our analysis, captures all the variation in children's outcomes between 1998 and 2001 specific to the treatments. The set of covariates includes demographics of the children and their parents (e.g. age, sex and schooling), some characteristics of the household (e.g. number of permanent members, location and house ownership), productive assets (business ownership, land to cultivate), state effects and dummies for pre-shock programs of social assistance at the municipality level. $Z$ is a sub-set of the vector X with household demographics (e.g. sex, age) and household composition variables (e.g. female-headed households) for which we estimate potential differential treatment effects, namely $\beta_4$. All the models were estimated using four different methods: OLS, probit (for outcomes of binary nature), fixed effects (conditional logit fixed effects for binary outcomes) and random effects. We also run several specifications for each method of estimation in order to check both the sensitivity of our results and test for some potential sources of bias. For simplicity, we report the coefficients of the parameters of interest for only two of these specifications (OLS and probit).

Table 5 reports the estimates of the interaction between the year dummy and the treatment dummy, namely the causal parameter $\beta_3$ from the reduced-form models in (6). Restricting the analysis and interpretation of our findings once again to the sample of rural children, all results obtained from the simple DID estimation remain significant and quantitatively large. The only qualitative change is related to children's school enrollment, as discussed above. In particular, conditioning on the set of covariates described before, we find no significant effect of Mitch on school enrollment. Labor force participation, on the other hand, increased by 58% among affected children due to the storm. Similarly, the proportion of children that was simultaneously enrolled in school and working more than doubled, going from 7.5% to 15.6% In terms of health, we find parallel results. The hurricane made children in affected areas over 30% less likely to be taken for medical consultation conditional on being sick, even though there was no significant difference on disease prevalence between affected and non-affected children. In addition, due to Mitch, children who directly suffered the shock were 8.7 percentage points more likely to be undernourished than before –more than three times the pre-shock rate- and their overall distribution of nutritional status worsened significantly.

### 4.3 Robustness Checks

We conduct a series of empirical exercises in order to further test the robustness of the causal effect identified in our research design. As documented in Section 2, disruptions to schooling and health services after Mitch appear not to have been severe. In spite of that, one concern may remain in terms of the non-exogenous response of the public authorities and emergency relief groups to the disaster as the flow of aid was largely correlated with the treatment status of the households and probably with some of the outcomes of their children. Actually it is straightforward to sign the direction of this bias since households were better off with these transfers as they would have been otherwise. As with the other potential confounders discussed in the identification section, although this sort of bias leads to an underestimation of the real Mitch effect, the coefficients are still very informative. However, the 1998 and 2001 surveys have a full set of questions that can be used to identify those households that benefited from several post-disaster programs of assistance (e.g. construction or reconstruction of schools, health centers, water sanitation, electricity, streets, roads and dwellings, employment programs, health campaigns and in-kind transfers such as food and medicines). We use this information to construct a group of dichotomous variables to account for the availability of these programs in 2001. Although these indicators are outcomes themselves, they are added to the right hand side of our regression equations to check the sensitivity of our estimates to their inclusion. As expected, coefficients are lower, but just slightly different from those obtained without these additional binary variables.[19]

The models are also run on alternative sub-samples as an attempt to simulate a cleaner quasi-experiment: one such sub-populations are rural households growing the same crops at the pre-shock time. In principle, this approach allows us to look at more comparable households by controlling for confounding factors such as differences in soil, crops' resilience to the shock as well as the intensity of exposure to the storm arising from varying altitude. To implement this idea, we restrict the units of analysis to children in rural households that grow the three main crops in the sample, namely corn, beans and rice. A potential caveat of this approach stems from the fact that systematic differential price trends across experimental groups can arise as a result of the hurricane, if the shortage of these products in treated regions allowed control households to benefit from higher prices. However, imports records from Nicaragua suggest that local scarcity is not very likely to contaminate these results as the domestic consumption of corn, beans and rice depends to a large extent from international markets and prices.

The estimates from the multivariate analysis on these sub-samples are analogous to the ones discussed above and are summarized in Table 6. Evidently, the price of this strategy is a significant reduction in the number of observations and, as a result, less precise estimates. In spite of that, the magnitudes of the coefficients remain similar to those previously described, particularly among children in corn-growing households (largest sample size). More importantly, the direction of the effects of the hurricane stays the same: Mitch is associated with a significant increase in child labor force participation, and a worsening of nutritional outcomes among children in affected areas even after controlling for the type of crop grown by households.[20]

---

[19] For instance, the increase of child labor identified for treated children drops from 0.085 to 0.083 with this new specification. The results of these models are not presented in the document for brevity but are available upon request.

[20] No results are presented for health consultations because the number of observations, after conditioning for being ill, is too small to obtain any meaningful inference.

We also use non-parametric methods to test whether our findings are heavily dependent on the linear specification assumed in the preceding econometric models. More specifically, we implement DID propensity score matching to both relax the linear from assumption and make our control and treatment groups more comparable by balancing their distributions of observables. Regarding the latter issue, the placement of the hurricane was an exogenous event close to be orthogonal to the error term but yet correlated with observables as discussed in Section 3. Given this, the properties of the non-parametric double difference analysis make this method particularly useful to identify the parameter of interest.

Pre-shock household covariates in the treatment status logistic regression include location (rural or urban), municipality, income per capita, parental education, distance to closest school and health center, as well as dichotomous variables to identify households owning a dwelling, businesses and land to crop. Several specifications of the propensity score are estimated jointly with different types of kernel to match children between the treatment and control groups.[21] In general, the findings hold, as the estimates are again significant and quantitatively large, and similar in magnitude to those obtained above –especially in terms of labor force participation, joint school attendance and labor force participation, as well as for nutritional status (Table 7).

So far, by using DID, we have made the identifying assumption that, in the absence of the weather shock, the control and the experimental groups would have followed similar trends of investment in children. While one cannot estimate the counterfactual of what the investment would have been had there been no Hurricane Mitch, we use the 1993 LSMS to analyze whether there was any differential trend between the two groups before 1998. The 1993 LSMS is not a panel with the 1998, 1999 and 2001 surveys and the construction of the sample segments between the 1993 and 1998 datasets do not have any matching correspondence. Consequently, the treatment status had to be redefined for these exercises and households in municipalities with segments interviewed in the 1999 LSMS were classified as part of the treatment group, with the remaining households comprising the control group. This new assignment rule is not expected to change dramatically the

[21] Notes of Table 7 explain the variables and methods used to estimate the propensity score in detail.

construction of our experimental samples, especially for rural areas, as most of the segments in these municipalities were re-interviewed in 1999. [22]

First, we test the "pre-treatment" trends by looking at some key determinants of children's outcomes using the pseudo panel at the municipality level for the period 1993-1998 (Table 8). Overall, simple DID estimates suggest that there were no differential changes in demographic characteristics or community-level variables between the two groups that could be driving the changes in investment in children observed between 1998 and 2001. Although there is an increase in the distance to the closest school and health center for treatments over controls, the magnitude is very small (around 5 and 3 minutes, respectively) and can hardly cast doubts on our results.

Next, we analyze whether there is any indication of a differential trend in the outcome variables between our two experimental groups prior to 1998. Our DID approach is more likely to have identified the causality of the shock if the "treatment effect" is not observed between 1993 and 1998. The results from the raw and extended placebo DID on the pseudo panel (presented in the lower panel of Table 8) support this assertion by revealing no sign of a differential trend in the outcomes of interest since most estimates are not statistically significant for either the total sample or for the rural one. The coefficients in one of the models of health care utilization (-0.204, P>0.235) and z-scores of weight-for-height (-0.212, P>0.132), however, reveal a differentially, but not significant, worsening in the mean of the treated households over the comparison group between 1993 and 1998. In order to further test these growth rates in the pre-shock period, we combine the three surveys (1993, 1998 and 2001) to estimate difference-in-difference-difference models for rural households between 1993 and 2001. The results, presented in Table 9, indicate that the large and still significant adverse effects of Hurricane Mitch –particularly on child labor force participation and nutrition– remain after removing group-specific pre-shock trends.

Attrition does not seem to be a contaminating issue for our identification strategy either. For households with children, there is a 20% attrition rate among treated households and 26% among

[22] In 1993 we only use the municipalities included in the 1998 survey and, for the pseudo DID, we classify a household as part of the treatment group if it is located in a municipality that in 1999 was surveyed (and, therefore, considered affected by Mitch). This definition of treatment ends up being remarkably close to the one used in the main analysis, since the 1999 LSMS contained 40 municipalities with an average of 13.65 households and 42 census segments with an average of 13 households (i.e. the municipalities' and segments' size was very similar), and, as a result, most households within each municipality are also within the same census segment.

control households between 1998 and 2001; however, for both groups, households that left the sample have similar observable characteristics between treated and controls –except for a bigger proportion of children between 6 and 15 years of age and older household heads among the leavers of the treated group. The unbalance in those two dimensions can hardly drive our findings. Even in the extreme case of some endogenous attrition of this sort, the potential biases may offset each other as households with relatively fewer dependents may do better while, on the other hand, younger household heads may do worse (e.g. less job market experience). In contrast, it may be that credit constrained households were more likely to stay as they lacked the resources needed to migrate. Although this can confound our estimates, we do not find evidence that some pre-shock determinants of access to credit and insurance differ statistically between the leavers and not leavers of the treatment and control groups. We also check whether those households more strongly hit by the hurricane were more likely to migrate. We compare the ratio of agricultural losses to pre-shock wealth among leavers and not leavers and find no evidence that the intensity of the shock was part of the reason to migrate among affected.[23]

In short, our results can only be contested if there is an unobservable difference between the two experimental groups or another change –not related to the shock and not accounted for in our research design– that affected the groups differently and that also happened between 1998 and 2001. Since the trajectory of Mitch was quite random, largely exogenous and affected different and non-contiguous municipalities of Nicaragua, this seems unlikely.

## 5. Intra-household Behavioral Context

The evidence presented in this paper may have important theoretical implications for the economic literature on household decision-making models. We have shown that children affected by a large shock in Nicaragua suffered significant negative consequences in terms of health and child labor, even three years after the disaster. Several reports on the hurricane and our own calculations suggest that disruptions to the supply of schooling and health services can hardly explain the observed deterioration of these outcomes in the middle-run. The question then arises of why we see

[23] A more detailed analysis on attrition and migration is available from the authors upon request.

this outcome. In particular, did children's nutrition worsen because their parents were left without enough income to feed all members of the family? Or was it the case that children were disproportionately affected vis-à-vis other members of the household? If one were to find evidence for the latter, then it may be the case that the traditional assumption of parents being good agents for children in the household decision-making process is simply not appropriate in some settings. The aftermath of a large shock may leave children at a disadvantage within the household, making them more vulnerable than adults in these events.[24] Since children represent the future human capital of a country, this result may call, in turn, for governments, NGOs and international organizations to provide in-kind aid targeted towards children (e.g. in-school food programs) or to create incentive schemes for parents to keep children in school and out of the labor market (e.g. conditional transfers) after a natural disaster.

To shed light on these behavioral responses, first we look at the impact of the storm on the consumption levels of adult goods in rural households. For this, we use the LSMS surveys used through out this paper which contain detailed information on the consumption basket of all households. In order to define what adults' goods are, we compare the composition of the consumption basket of childless households with that of households with children. The goods for which their representation in the consumption basket in childless households is statistically higher than in those with children are considered adult goods. Following this definition, tobacco and alcohol are considered adult goods.

Table 10 summarizes the main results from this exercise. We find that there is no differential change in the consumption of tobacco and alcohol between treatment and control groups. That is, the consumption share of adult goods does not seem to have been significantly affected by Mitch. In fact, the coefficients, although not statistically significant, show an increase in the consumption of tobacco due to the storm. Notwithstanding that adult and children goods may not be directly comparable because of different elasticities of demand, this exercise suggests that children may have been relatively worse off than adults within families affected by the shock.

[24] Hoddinott and Kinsey (1998, 2000), in two different papers, look at the impact of the 1994-95 drought in Zimbabwe and find that women and young children's nutritional status was adversely affected by the event, but not men's. In particular, they find that children ages 12-24 months lost an average of 1.5-2.0 centimeters of linear growth after the drought. For women, however, the loss of body mass was only temporary.

We use a second approach to get at the differential effect of Hurricane Mitch on households' members by focusing on nutrition. The LSMS datasets do not include anthropometric information for adults, and therefore we cannot know what happened to adults' nutrition after Hurricane Mitch in the households we look at in this paper. Instead, we use the Demographic Health Surveys (DHS) for Nicaragua, a cross-sectional survey that includes anthropometric information for children and their mothers and that was carried out in 1998 and in 2001 to construct a pseudo-panel at the municipality level.[25] In this new dataset, we analyze the effect of Mitch on mothers' body mass index and weight/height indicator, two measures that are suitable to capture changes in adult nutritional status (Table 10). We find that the effect on adult's nutrition is close to zero and not statistically significant. That is, using measures associated with adults' consumption and well-being, we do not find evidence suggesting a negative impact of Hurricane Mitch –contrary to our main results in relation to children.

These results have important implications for the nature of the allocation process in the household. On the one hand, models of intra-household allocation of resources have long stressed that unitary models of household preferences may not properly represent the way decisions are made in the household and that, hence, these models may lead to wrong conclusions. On the other hand, collective models try to address some of the shortcomings of the unitary framework but usually assume parents are altruistic towards their children well-being (either because they have an altruistic interest in the children themselves or due to the idea that children's health is related to future output and a rent for the parents), still if there is some bargaining process between the parents. However, if children are disproportionately affected in the aftermath of a shock, even the existing collective models may not tell the whole story.

Even if it is optimal for the household as a whole, given the existing credit and insurance constraints, to take children out of school, push them into the labor market and/or direct fewer resources towards their nutrition and health care, there may be space for public action on behalf of the children. This is an interesting and important avenue for research in the future. From a

[25] The DHS and the LSMS for 1998 and 2001 used the same sample framework and, therefore, information from the two samples can be used together. Also, both surveys used the same scales and measuring devices for the anthropometric data (World Bank, 2002). For more information on the results discussed in this section, please contact the authors.

theoretical point of view, it suggests a need to revise our assumptions on household decision models and, specifically, the importance of children's utility on their parents' objective functions. From a policy perspective, it highlights that issues of targeting of post-disaster aid do not only exist at the level of communities and households but of individuals since children seem to be a especially vulnerable group of the population.

## 6. Conclusions

The existing economic literature strongly suggests that the capacity of households in poor countries to smooth consumption across time and states of nature is limited. This seems to be especially true in the case of large generalized shocks such as natural disasters, when some of the informal mechanisms of risk-sharing become less widespread. Agricultural populations, especially, are vulnerable to this type of generalized weather-related shocks and households are exposed, therefore, to significant uncertainties. And although some studies exist on the macroeconomic effects and the direct losses associated with natural disasters, the literature on the welfare implications of these phenomena at the household level is rather limited. In particular, work on the consequences of these shocks for children, in terms of the investment in their health and their education, is quite scarce. Since Hurricane Mitch was largely unanticipated and hit only some areas of the country, it constitutes a unique natural experiment setting for the study of households' responses to this sort of shocks.

Using a quasi-experimental design, this paper has presented evidence on the pervasive medium-run effects of Hurricane Mitch on children's well-being in Nicaragua. Children in areas directly affected by the storm were 30% less likely to be taken for medical consultation conditional on being sick, even though there was no significant difference on the prevalence of illness between affected and non-affected children. Furthermore, children in regions hit by Mitch were 8.7 percentage points more likely to be undernourished and the overall distribution of nutritional status among children in these areas –especially of those in the tail of the distribution– worsened significantly as a result of the storm. On the other hand, while we find no significant effect of Mitch on school enrollment, labor force participation increased by 58% among children in areas affected by the hurricane. Similarly, the proportion of children simultaneously enrolled in school and working more than doubled due to Mitch, going from 7.5% to 15.6%. The magnitude of these effects is quite large.

When interpreting our results, it is important to take into account two considerations. First, the findings represent "lower-bound" estimates of the effects of Mitch. By using a difference-in-difference approach, we are attributing all the changes in our variables of interest in the control group to non-Mitch factors; however, the effects of a natural disaster no doubt spill over to all the population (especially in a small country), above all due to the known macroeconomic effects of such a large shock. Second, since we are looking at the effect of Mitch in 2001, almost three years after it hit Nicaragua, our results are illustrative of the medium-term effects of a natural disaster. Furthermore, since the items that we analyze are directly related to the earning potential of the children studied, these results are also very informative about the existence of important long-term effects of natural disasters at the household and individual levels.

The absence of more efficient mechanisms to deal with natural disasters puts households in a situation where they need to make difficult choices: which expenditures or investments to reduce? From a policy perspective, it is relevant to know what these choices are. This study indicates that children may be significantly affected after the needed reallocation of resources when assets and income drastically fall after a disaster. Furthermore, our study suggests that, within affected households, children are left relatively worse off since parents' nutrition and consumption patterns seem to be largely unaffected in the medium-term. This result provides useful insights for the theoretical literature on the nature of the resource allocation process in the household and parents' priorities when making spending and investment decisions after a large shock. Further studies that analyze the agency role of parents vis-à-vis their children in a wider context are in order.

This paper also has important implications for ex-ante and ex-post disaster relief programs. To the extent that disruptions in school enrollment and health deficiencies have long-term effects for individuals, households and the economy as a whole, our results highlight the need for a comprehensive agenda when dealing with the consequences of adverse shocks to include the possible effects on children. A one-time flow of aid after a large shock may not do enough to prevent the adverse longer term effects of such an event. Ambler (2005) and Lazo (2005) both find that post-disaster emergency aid after Mitch was not targeted at the poorest households –those which had suffered the largest asset losses relative to their initial wealth. Instead, post-disaster aid seemed to be directed towards the most affected regions without effective targeting within those areas. They conclude that better targeting and coordination among relief agencies is needed. Moreover, our findings suggest that if children are disproportionately affected after a natural disaster, simple ex-ante or ex-post cash transfers to households may not be enough to keep children in school and well-nourished. Ex-post targeted programs directed specifically towards maintaining school enrollment and assuring children are well-fed seem more appropriate. With this in mind, social programs like *Progresa* and others that provide food for children in schools may be particularly advantageous in the aftermath of natural disasters to mitigate the longer term adverse consequences of these shocks by creating strong incentives for parents to look after children's well-being.

Hence, large shocks, such as natural disasters, cause populations to suffer not only in the short run. The most destructive consequences of these events in poor countries may well fall on the country's future human capital stock, children, who may suffer long-term effects if natural disasters increase malnutrition and take them out of school. And the picture looks even grimmer if, in the absence of appropriate incentives, children are put at a disadvantage even within their own households as initial evidence discussed in this paper suggests.

**References**

Alderman, H. and C. Paxon, (1994), "Do the Poor Insure? A Synthesis of the Literature on Risk and Consumption in Developing Countries", in *Economics of the Changing World*, ed. Bacha, New York: St. Martin's, pp. 48-78.

Ambler, C., (2005), "The Distribution of Emergency Relief in Post Hurricane Mitch in Nicaragua", Thesis Project, Williams College, Williamstown, MA.

Anderson, M.,(2000), "The Impact of Natural Disasters on the Poor: A Background Note"., mimeo.

Angrist, J., G. Imbens and D. Rubin, (1996), ”Identification of Causal Effects Using Instrumental Variables”, *Journal of the American Statistical Association*, 91, pp. 444–55.

Angrist, J. and A. Krueger (1999), “Empirical Strategies in Labor Economics”, in O. Ashenfelter and D. Card, *Handbook of Labor Economics*, Vol. III. A., pp. 1277-1366.

Auffret, P., (2003), “High Consumption Volatility: The Impact of Natural Disasters?”, *World Bank Policy Research Paper 2962,* Washington, DC.

Basu, K. and P. Van, (1998), “The Economics of Child Labor”, *American Economic Review*, 88, pp. 412-427.

Barrera, F. and F. Pérez, (2005), “Consumption Smoothing: Empirical Evidence from Colombia and Nicaragua”, mimeo, Fedesarrollo, Bogota, Colombia.

Becker, G., (1974), “A Theory of Social Interactions”, *Journal of Political Economy* 82, pp. 1063 – 1094.

Beegle, Kathleen, R. Dehejia and R. Gatti, (2003), “Child Labor, Crops Shocks and Credit Constraints”, NBER Working Paper 10088.

Behrman, J., (1988), “Intra-household Allocation of Nutrients in Rural India: Are Boys Favored? Do Parents Exhibit Inequality Aversion?”, *Oxford Economic Papers*, 1988, vol. 40 (1), pp. 32-54.

Cardona, O., (2001), “El Impacto Económico de los Desastres: Esfuerzos de Medición Existentes y Propuesta Alternativa”, Secretariado Técnico de la Presidencia de la República Dominicana y el Banco Interamericano de Desarrollo.

Carranza, E., (2005), “Birth Order and Child Labor: Evidence from Peru”, mimeo, Kennedy School of Government, Harvard University.

Carter, M., P. Little, T. Mogues and W. Negat, (2004), “Shocks, Sensitivity and Resilience: Tracking the Economic Impacts of Environmental Disaster on Assets in Ethiopia and Honduras”, Department of Agricultural & Applied Economics, Staff Paper No. 489, University of Wisconsin.

Charveriat, C., (2000), “Natural Disasters in Latin America and the Caribbean: An Overview of Risk”, *IADB Working Paper*, No. 434, Inter-American Development Bank, Washington, DC.

Guha-Sapir, D., D. Hargitt and P. Hoyois, (2003), *Thirty Years of Natural Disasters. 1974-2003: The Numbers*, UCL Presses Universitaires de Louvain, Centre for Research on the Epidemiology of Disasters (CRED), Brussels.

Deaton, A., (1992), “Saving and Income Smoothing in Cote d’Ivoire”, *Journal of African Economies*, l (1), pp. 1-23.

Deaton, A., (1997), *The Analysis of Household Surveys. A Microeconomic Approach to Development Policy*, Johns Hopkins University Press, Baltimore, Maryland.

Donald, S. and K. Lang, (2001), “Inferences with Difference in Differences and other Panel Data”, Boston University, working paper.

Economic Commission for Latin American and the Caribbean, ECLAC, (1999), "Nicaragua: Evaluación de los Daños Ocasionados por el Huracán Mitch, 1998. Sus Implicaciones para el Desarrollo Económico y Social y el Medio Ambiente".

Fafchamps, M. and S. Lund, (2001), "Risk-Sharing Networks in Rural Philippines", working paper.

Falkner, F. and J. Tanner, (1986), *Human Growth: A Comprehensive Treatise*, Vol. 3, New York: Plenum.

Filmer, D., E. King and L. Pritchett, (1998), "Gender Disparity in South Asia: Comparisons between and within Countries".

Foster, A., (1995), "Prices, Credit Markets and Child Growth in Low-Income Rural Areas", *Economic Journal 105 (430)*, pp. 551-70.

Freeman, P., (2000), "Estimating Chronic Risk from Natural Disasters in Developing Countries: A Case Study on Honduras", Paper for the Annual Bank Conference on Development Thinking at the Millennium, June 26-28, World Bank, Washington, DC.

García-Verdú, R., (2002), "Evaluation of Conditional Income Support Programs: The Case of Mexico's PROGRESA", Doctoral Dissertation, University of Chicago.

Guarcello, L., F. Mealli and F. Rosati, (2004), "Household Vulnerability and Child Labor: the effects of shocks, credit rationing, and insurance", UNICEF.

Hiscock, J., (2005), "Tsunami Disaster: Recovery Hurricane Mitch", *The Independent*, January 2005.

Hoddinott, J. and B. Kinsey, (2001), "Child Growth in the Time of Drought", *Oxford Bulletin of Economics and Statistics*, 63 (4), pp. 409-436.

Hoddinott, J. and B. Kinsey, (2000), "Adult Health in Time of Drought", Food Consumption and Nutrition Division, Discussion Paper 79, International Food Policy Research Institute, Washington, D.C.

International Red Cross, (2005), *World Disasters Report – Focus on Information in Disasters*, Geneva, Switzerland.

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

Jensen, R., (2000), "Agricultural Volatility and Investments in Children", *American Economic Review* 90 (2), pp. 399 -404.

Lazo, C., (2005), "Equity in the Provision of Aid after a Natural Disaster: Household Evidence from Nicaragua", Master Thesis, Kennedy School of Government, Harvard University.

Lucas, R. and O. Stark, (1985), "Motivations to Remit: Evidence from Botswana", *Journal of Political Economy* 93, pp. 901-918.

Mckinley, J. and W. Stevens, (1998), "When Nature Rages: A Special Report; the life of a hurricane, the death that it caused", *The New York Times*, 9 November, p. A1, col. 2.

Morduch, J., (1995), "Income Smoothing and Consumption Smoothing", *Journal of Economic Perspectives* 9 (3), pp. 103-114.

Morduch, J., (2003), "Consumption Smoothing Across Space: Tests for Village-Level Responses to Risk", Stefan Dercon, ed., Insurance Against Poverty, Oxford University Press.

Nicaraguan National Institute of Statistics and Censes (INEC), (2000), "Comparative Indicators in Zones Affected by Hurricane Mitch, according to Household Surveys".

Nicaraguan National Institute of Statistics and Censes (INEC), (2002), "Encuesta Nacional de Hogares sobre Medición de Niceles de Vida 2001: Manual de Usuario de la Base de Datos".

Organization for Economic Co-operation and Development (OECD), (2004), "Geographical Distribution of Financial Flows to Aid Recipients", Paris.

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

Platteau, J., (1991), "Traditional Systems of Social Security and Hunger Insurance: Past Achievements and Modern Challenges", in Ahmad, E. et.al (eds.) Social Security in Developing Countries, Clarendon Press, Oxford.

Rosenzweig, M., (1988), "Risk, Implicit Contracts, and the Family in Rural Areas of Low-Income Countries, *Economic Journal* 98 (393), pp. 1148 – 1170.

Rosenzweig, M. and O. Stark, (1989), "Consumption Smoothing, Migration and Marriage: Evidence from Rural India", *Journal of Political Economy,* 97 (4), pp. 905-927.

Santos, I., (2006), "Risk-Sharing and the Role of Inter-Household Transfers after a Natural Disaster. Evidence from Hurricane Mitch in Nicaragua", draft, doctoral dissertation, Kennedy School of Government, Harvard University.

Skoufias, E., (2001), "Progresa and Its Impacts on the Human Capital and Welfare of Households in Rural Mexico", Research Report 139, International Food policy Research Institute, Washington, DC.

Townsend, R., (1994), "Risk and Insurance in Village India", *Econometrica* 62 (3), pp. 539-92.

Udry, C., (1990), "Credit Markets in Rural Nigeria: Credit as Insurance in a Rural Economy", *World Bank Economic Review,* Vol. 4, No. 3, pp. 251-269.

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

Ureta, M., (2005), "Hurricane Mitch, Family Budgets and Schooling in Nicaragua", draft, College Station, Texas.

Urroz, A., M. Aranda and C. Morales, (1999), "El Huracán Mitch en Nicaragua"in *Cronicas del Desaster*, document 12141, Washington D.C.

World Bank, (2001a), "Nicaragua Living Standards Measurement Study Survey. Post-Mitch Survey 1999", Supplemental Information Document, Washington, DC.

World Bank, (2001b), "Nicaragua Poverty Assessment: Challenges and Opportunities for Poverty Reduction", Report No. 20488-NI. Washington, DC

World Bank, (2001c), *World Development Report 2000/2001: Attacking Poverty*, Washington, DC.

World Bank, (2002a), "Nicaragua Living Standards Measurement Study Survey 1998", Basic and Supplemental Information Document, Washington, DC.

World Bank, (2002b), "Nicaragua Living Standards Measurement Study Survey 1993 Documentation", Washington, DC.

# Appendix

## 1. Household-decision making model

We use a simple uni-temporal decision model –capturing the same sort of effects as those from a dynamic framework– with full information and a unitary household. Parents care about the level of consumption of the household (*C*) and the future earnings of the children (*E*). That is, in this model, parents care about the "quality" of the children only indirectly because they will receive a fraction $\phi$ of the future earnings of their children. Parents, then, maximize the following utility function:

$$\max U = U(C, E), \tag{1}$$

where $U^{'}(\bullet) > 0$ and $U^{''}(\bullet) < 0$ for both arguments.

For simplicity, we combine education and health in human capital. Human capital has two components: *S*, which represents the stock of human capital at the beginning of the period; and *H*, which is the investment in human capital in the period. We are interested in understanding the effects of the shock on the flow of children's human capital (*H*), rather than on the existing stock (*S*), since the objective is to find out how investment in children changed after the shock. Therefore, in the empirical section, we use school enrollment, short-term nutritional status (indicated by weight for height), use of health facilities (conditional on being sick), and labor supply as our main outcomes of interest.

The "quality" of the children (i.e. their future earnings) is assumed to be a linear combination of the amount of human capital (*S*+ *H*) and their innate abilities, as well as their health endowment ( $\chi$ ), such that:

$$E = \alpha(S + H) + \beta\chi, \tag{2}$$

where $\alpha$ and $\beta$ are the contributions of human capital and genetics, respectively.

Human capital investment depends on complementary goods and services, such as books and vaccines, *X*; the time the child spends in school or medical care, $t_H^c$ ; and the time that parents dedicate to investment in each child's quality, $t_H^p$. The marginal effects of *X*, $t_H^c$ and $t_H^p$ on human capital are assumed to be positive. Similarly, human capital investment depends on a set of observed characteristics of the child, $\theta$ (including gender, age, birth order, among others); unobserved characteristics of the child, $\chi$, (health endowment or innate abilities) and finally, $\delta$, which captures parental education and community characteristics such as the availability of health centers and schools, prices, environmental factors, among others. The reduced form of the human capital investment in the child can then be represented as follows:

$$H = H(X, t_H^c, t_H^p; \theta, \chi, \delta) \qquad (3)$$

At the optimum, household expenditures will equal household income and assets. Expenditures have two components: the consumption of the household (excluding goods and services related to human capital), *C* (numeraire), and the consumption of goods and services related to human capital, $p_x XN$ (where $p_x$ denotes the vector of prices of "human capital" goods and *N* is the number of children in the household).

The resources of the household include assets (*A*) and income. There are four different sources of income: non-labor income of the household ($Y_{nl}$), labor income of all children today ($W^c(T - t_H^c)N$), labor income of the parents ($W^p(T - Nt_H^p)$) and a fraction of the labor income of adult children ($\phi N_A E$). Labor income of each child is equal to his wage ($W^c$) multiplied by the number of time units he dedicates to work (i.e. the difference between the total time endowment and the time spent in school or medical care). An important characteristic of this model is, therefore, that it allows for the possibility of a child to be both enrolled in school and working, a relevant aspect given the characteristics of child labor in Nicaragua. The labor income of the parents, similarly, is equal to their wage ($W^p$) times the number of time units they dedicate to work. Bringing these elements together, the budget constraint of the household is:

$$C + p_x XN = Y_{nl} + W^c(T - t_H^c)N + W^p(T - Nt_H^p) + \phi N_A E + A \qquad (4)$$

Therefore, households maximize utility (1) subject to restrictions (2) – (4), by choosing the appropriate levels of consumption (*C*), time allocated to human capital ($t_H^c, t_H^p$), and consumption of goods and services complementary to human capital investment (*X*). The first-order conditions of this maximization problem are the following:

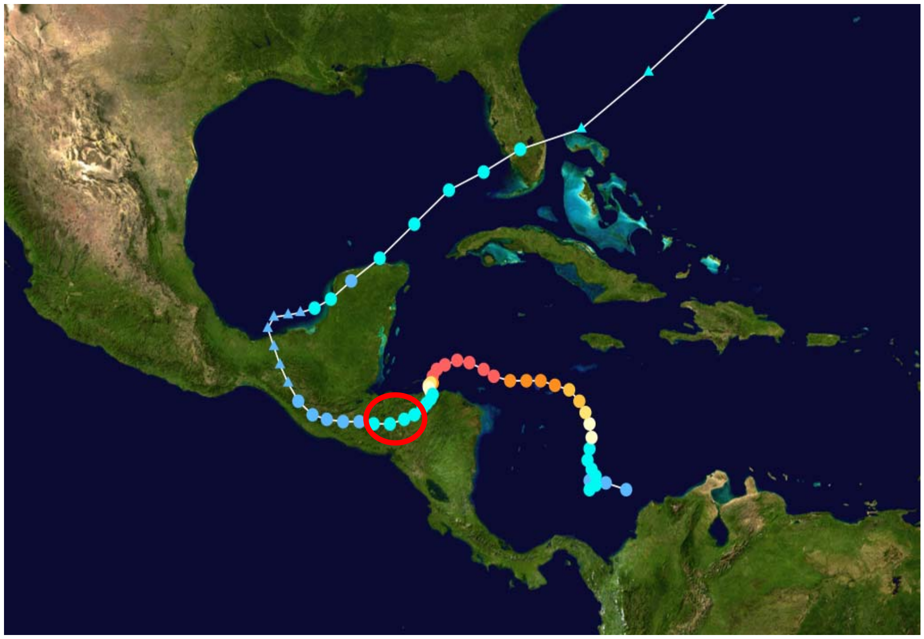
$$MRS_{CE} = \frac{U_E}{U_C} = N\left(\frac{W^C}{\alpha H t_H^c} - \phi\right) = MC_{t_H^C} \tag{5}$$

$$MRS_{CE} = \frac{U_E}{U_C} = N\left(\frac{W^p}{\alpha H t_H^p} - \phi\right) = MC_{t_H^p} \tag{6}$$

$$MRS_{CE} = \frac{U_E}{U_C} = N\left(\frac{P_X}{\alpha H_x} - \phi\right) = MC_X \tag{7}$$

At the optimum, the marginal rate of substitution between household consumption and child quality equals the marginal cost of investing in the human capital of the child. Combining the first-order conditions yields the solution to the problem: the household will maximize utility by setting the marginal cost associated with the time of the child, the time of the parents and the consumption of "human capital" goods and services all equal. Regarding the predictions of the model, the direct effects will be translated into a higher marginal cost of the goods and services needed for accumulating human capital and then into lower investments. The indirect effects happen through income, some of them negative and other positive as explained in the text. Finally, the secondary effects are mainly changes in wages and entail both income and substitution effects that go in opposite directions. Although the direct effects can accurately predict a negative impact on children's human capital, the indirect and secondary effects as a whole can either reinforce or diminish such deterioration.

## 2. Trajectory of Hurricane Mitch (October 20-November 9, 1998)



Source: The background image is from NASA. Tracking data from the National Hurricane Center

## Trajectory of the Eye of Hurricane Mitch in Nicaragua (October 27-31, 1998)

## Table 1. Microeconomic Effects of Hurricane Mitch 1999

| Variable | (%) | Variable | (%) |
|---|---|---|---|
| Did the family move to another house? | 17.3 | After Mitch, this household benefited from assistance programs like: | |
| Was this house temporaly vacant? | 29.4 | New school/Reconstruction | 5.8 |
| During this time, the family moved to? | | New health center/Reconstruction | 2.2 |
| Refugee | 35.5 | Water provision | 1.7 |
| Relatives' home | 55.8 | Sewage | 0.0 |
| Temporary home | 7.3 | Electricity | 1.5 |
| Other municipality | 1.5 | Latrine | 7.2 |
| Other state | 1.5 | Food | 45.3 |
| Other country | 0.75 | Health programs | 38.1 |
| The house/basic services were affected in some way | 45.8 | Employment programs | 17.1 |
| Structure of ….. in the household was totally/partially destroyed | | Donation of clothing | 19.7 |
| Walls | 56.7 | Donation of medicines and/or water | 9.2 |
| Floor | 19.5 | Donation of house | 1.7 |
| Roof | 58.6 | A member of the household died due to Mitch | 1.8 |
| Water | 41.8 | Didn't go to the doctor because health center was destroyed | 0.3 |
| Toilet | 61.7 | Didn't work because source of employment was destroyed | 3.3 |
| Electricity | 24.0 | Distance from your previous house in kilometers | 4.1 |

*Notes*. % refers to the percentage with respect to the total number of households (595) included in the 1999 post-Mitch LSMS survey.

## Table 2. Agricultural Losses Due to Hurricane Mitch 1999

| Type of Loss | % of households [1] | Average Loss (cordobas) [2] | Avergae Loss [3] |
|---|---|---|---|
| A.Agricultural property | 9.20% | $8,171.67 | $406.55 |
| B. Crops | 96.63% | $4,195.97 | $2,191.92 |
| C. Agricultural equipment | 2.15% | $8,271.43 | $96.02 |
| D. Agricultural installations | 6.75% | $2,669.36 | $97.39 |
| E. Animals for work | 10.43% | $432.15 | $24.37 |
| F. Other | 7.43% | $3,512.35 | $116.50 |
| Total agricultural losses | | $5,418.17 | $2,932.75 |

*Notes*: (1) Percentage of households who own land and who were affected by Mitch, (2) Average losses per household in córdobas, conditional on having suffered a loss on the specified category, (3) Average losses per household in córdobas , not conditional on having suffered a loss or owning land (losses=0 if no losses).

**Table 3. Pre-Shock Summary Statistics by Treatment Status**

| Variable | Total Sample | | | | Rural Sample | | | |
|---|---|---|---|---|---|---|---|---|
| | Total | Treatment (Mitch=1) | Control (Mitch=0) | Difference | Total | Treatment (Mitch=1) | Control (Mitch=0) | Difference |
| Number of members per household | 6.06 | 6.19 | 6.04 | 0.149 | 6.39 | 6.56 | 6.34 | 0.220 |
| | [0.052] | [0.144] | [0.056] | [0.154] | [0.079] | [0.173] | [0.089] | [0.195] |
| Number of children per household | 2.60 | 2.65 | 2.59 | 0.058 | 2.93 | 2.90 | 2.94 | -0.037 |
| | [0.037] | [0.100] | [0.039] | [0.107] | 0.06 | [0.123] | [0.066] | [0.140] |
| Age: 0-6 years | 1.11 | 1.14 | 1.11 | 0.032 | 1.32 | 1.28 | 1.32 | -0.039 |
| | [0.021] | [0.059] | [0.023] | [0.063] | [0.033] | [0.074] | [0.030] | [0.083] |
| Age: 6-15 years | 1.49 | 1.51 | 1.48 | 0.025 | 1.62 | 1.62 | 1.62 | 0.006 |
| | [0.025] | [0.068] | [0.027] | [0.073] | [0.040] | [0.082] | [0.045] | [0.094] |
| Proportion of female children | 0.501 | 0.522 | 0.498 | 0.024 | 0.50 | 0.517 | 0.491 | 0.026 |
| | [0.006] | [0.017] | [0.007] | [0.019] | [0.009] | [0.019] | [0.010] | [0.022] |
| Age of household head | 45.29 | 45.46 | 45.27 | 0.197 | 44.76 | 45.46 | 44.56 | 0.903 |
| (in years) | [0.285] | [0.772] | [0.307] | [0.831] | [0.429] | [0.929] | [0.484] | [1.048] |
| Age of children | 7.56 | 7.70 | 7.53 | 0.163 | 7.30 | 7.63 | 7.20 | 0.425 * |
| (in years) | [0.069] | [0.194] | [0.074] | [0.208] | [0.098] | [0.215] | [0.110] | [0.242] |
| Years of schooling: head of household | 4.10 | 2.93 | 4.28 | -1.359 *** | 2.45 | 2.18 | 2.52 | -0.346 * |
| | [0.082] | [0.175] | [0.090] | [0.197] | [0.090] | [0.165] | [0.105] | [0.196] |
| Years of schooling: spouse | 3.99 | 2.89 | 4.191 | -1.303 *** | 2.55 | 2.40 | 2.60 | -0.202 |
| | [0.089] | [0.186] | [0.099] | [0.211] | [0.096] | [0.187] | [0.112] | [0.198] |
| Proportion of households headed | 0.272 | 0.196 | 0.285 | -0.089 *** | 0.183 | 0.153 | 0.192 | -0.039 |
| by women | [0.008] | [0.02] | [0.009] | [0.022] | [0.010] | [0.021] | [0.012] | [0.024] |
| Proportion of rural households | 0.462 | 0.722 | 0.419 | 0.303 *** | ---- | ---- | ---- | ---- |
| | [0.009] | [0.022] | [0.010] | [0.024] | | | | |
| Annual income per capita | 5,864 | 3,382 | 6,279 | -2,897 *** | 3,217 | 2,613 | 3,391 | -777.9 * |
| (Mean in 1998 Cordobas) | [418.0] | [261.2] | [485.4] | [551.3] | [272.0] | [275.1] | [341.2] | [438.3] |
| Annual income per capita | 3,141 | 1,836 | 3,425 | -1,588 *** | 1,590 | 1,451 | 1,615 | -164.2 |
| (Median in 1998 Cordobas) | [284.9] | [185.2] | [305.4] | [342.3] | [226.3] | [212.0] | [236.1] | [185.5] |
| Proportion of households that | 0.496 | 0.439 | 0.506 | -0.067 *** | 0.430 | 0.390 | 0.442 | -0.052 |
| own dwelling | [0.009] | [0.024] | [0.010] | [0.027] | [0.013] | [0.028] | [0.015] | [0.032] |
| Distance to closest health center | 13.95 | 16.58 | 13.49 | 3.08 *** | 14.68 | 16.93 | 14.00 | 2.93 *** |
| (minutes) | [0.104] | [0.315] | [0.109] | [0.334] | [0.177] | [0.375] | [0.200] | [0.426] |
| Distance to closest primary school | 11.23 | 13.57 | 10.83 | 2.74 *** | 13.94 | 14.95 | 13.65 | 1.30 *** |
| (minutes) | [0.085] | [0.249] | [0.090] | [0.265] | [0.144] | [0.301] | [0.165] | [0.343] |
| Number of households | 2,764 | 396 | 2,368 | | 1,279 | 286 | 993 | |

*Notes*. Standard errors presented in square brackets. Bootstrapped standard errors of median income obtained from 200 replications. The symbols ***, (**) and [*] stand for significance at the 1%, (5%) and [10%] levels, respectively. Approximately 15% of the total number of households represents the experimental group. See text for definitions of experimental and non experimental households.

## Table 4. Difference-in-Difference Reduced Form Estimates of the Impact of the Shock on Investments in Children

| Group | School attendance | | | | | | Child labor force participation | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Total Sample | | | Rural | | | Total Sample | | | Rural | | |
| | Before Mitch | After Mitch | 2001-98: | Before Mitch | After Mitch | 2001-98: | Before Mitch | After Mitch | 2001-98: | Before Mitch | After Mitch | 2001-98: |
| **Treatments** | 0.741 | 0.859 | 0.118 | 0.699 | 0.834 | 0.135 | 0.161 | 0.220 | 0.059 | 0.185 | 0.225 | 0.040 |
| | [0.016] | [0.013] | [0.021] | [0.020] | [0.016] | [0.025] | [0.013] | [0.015] | [0.020] | 0.016 | [0.017] | [0.023] |
| **Controls** | 0.786 | 0.846 | 0.060 | 0.676 | 0.758 | 0.082 | 0.130 | 0.125 | -0.005 | 0.184 | 0.169 | -0.015 |
| | [0.006] | [0.005] | [0.008] | [0.011] | [0.010] | [0.015] | [0.005] | [0.005] | [0.008] | 0.008 | [0.008] | [0.012] |
| ***D* at a point in time:** | -0.045 | 0.013 | | 0.023 | 0.076 | | 0.031 | 0.095 | | 0.001 | 0.056 | |
| | [0.018] | [0.014] | | [0.023] | [0.019] | | [0.014] | [0.015] | | [0.018] | [0.019 | |
| ***D-D*** | 0.057 ** | | | 0.053 * | | | 0.064 *** | | | 0.056 ** | | |
| | [0.025] | | | [0.031] | | | [0.024] | | | [0.029] | | |
| **Observations** | 8,970 | | | 4,436 | | | 9,956 | | | 4,951 | | |

| Group | Both in school and the labor market | | | | | | Child with diarrhea? (children between 0 and 6) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Total Sample | | | Rural | | | Total Sample | | | Rural | | |
| | Before Mitch | After Mitch | 2001-98: | Before Mitch | After Mitch | 2001-98: | Before Mitch | After Mitch | 2001-98: | Before Mitch | After Mitch | 2001-98: |
| **Treatments** | 0.082 | 0.168 | 0.086 | 0.094 | 0.162 | 0.068 | 0.238 | 0.227 | -0.011 | 0.248 | 0.218 | -0.030 |
| | [0.010] | [0.014] | [0.017] | [0.006] | [0.016] | [0.020] | [0.020] | 0.022 | [0.030] | [0.022] | [0.025] | [0.034] |
| **Controls** | 0.073 | 0.086 | 0.013 | 0.092 | 0.097 | 0.005 | 0.198 | 0.224 | 0.026 | 0.239 | 0.263 | 0.024 |
| | [0.004] | [0.004] | [0.006] | [0.012] | [0.007] | [0.010] | [0.007] | 0.011 | [0.013] | [0.012] | [0.018] | [0.022] |
| ***D* at a point in time:** | 0.009 | 0.082 | | 0.002 | 0.065 | | 0.040 | 0.003 | | 0.009 | -0.045 | |
| | [0.011] | [0.015] | | [0.014] | [0.017] | | [0.021] | [0.025] | | [0.025] | [0.031] | |
| ***D-D*** | 0.073 *** | | | 0.066 ** | | | -0.036 | | | -0.054 | | |
| | [0.021] | | | [0.027] | | | [0.030] | | | [0.043] | | |
| **Observations** | 8,970 | | | 4,436 | | | 5,306 | | | 2,836 | | |

| Group | Health care utilization (children between 0 and 6) | | | | | | Health care utilization (children between 6 and 15) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Total Sample | | | Rural | | | Total Sample | | | Rural | | |
| | Before Mitch | After Mitch | 2001-98: | Before Mitch | After Mitch | 2001-98: | Before Mitch | After Mitch | 2001-98: | Before Mitch | After Mitch | 2001-98: |
| **Treatments** | 0.533 | 0.468 | -0.065 | 0.528 | 0.413 | -0.115 | 0.271 | 0.261 | -0.010 | 0.240 | 0.233 | -0.007 |
| | [0.048] | [0.056] | [0.074] | [0.053] | [0.065] | [0.084] | [0.029] | [0.027] | [0.040] | [0.031] | [0.030] | [0.043] |
| **Controls** | 0.527 | 0.667 | 0.140 | 0.474 | 0.652 | 0.178 | 0.323 | 0.421 | 0.098 | 0.264 | 0.354 | 0.090 |
| | [0.022] | [0.035] | [0.041] | [0.029] | [0.058] | [0.065] | [0.012] | [0.015] | [0.019] | [0.016] | [0.019] | [0.025] |
| ***D* at a point in time:** | 0.006 | -0.199 | | 0.054 | -0.239 | | -0.052 | -0.160 | | -0.024 | -0.121 | |
| | [0.053] | [0.062] | | [0.060] | [0.087] | | [0.031] | [0.031] | | [0.035] | [0.035] | |
| ***D-D*** | -0.205 ** | | | -0.292 ** | | | -0.107 *** | | | -0.097 ** | | |
| | [0.098] | | | [0.111] | | | [0.038] | | | [0.047] | | |
| **Observations** | 1,118 | | | 684 | | | 3,203 | | | 1,679 | | |

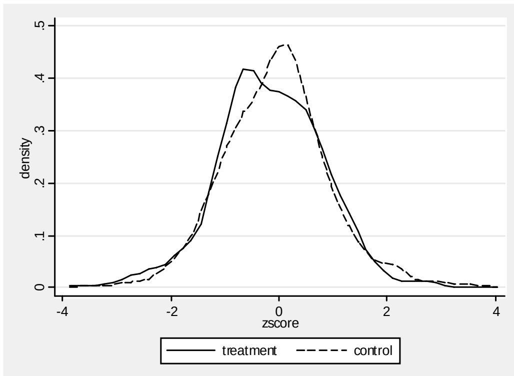
| Group | Z-score weight-for-height | | | | | | Children with severe undernutrition (<-2Z) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Total Sample | | | Rural | | | Total Sample | | | Rural | | |
| | Before Mitch | After Mitch | 2001-98: | Before Mitch | After Mitch | 2001-98: | Before Mitch | After Mitch | 2001-98: | Before Mitch | After Mitch | 2001-98: |
| **Treatments** | -0.156 | -0.400 | -0.244 | -0.133 | -0.377 | -0.244 | 0.037 | 0.098 | 0.061 | 0.042 | 0.102 | 0.060 |
| | [0.023] | [0.076] | [0.093] | [0.061] | [0.087] | [0.106] | [0.010] | [0.019] | [0.022] | [0.012] | [0.022] | [0.025] |
| **Controls** | -0.051 | 0.158 | 0.209 | -0.058 | 0.110 | 0.168 | 0.024 | 0.010 | -0.014 | 0.025 | 0.009 | -0.016 |
| | [0.053] | [0.025] | [0.034] | [0.032] | [0.036] | [0.049] | [0.003] | [0.002] | [0.004] | [0.005] | [0.003] | [0.006] |
| ***D* at a point in time:** | -0.105 | -0.558 | | -0.075 | -0.487 | | 0.013 | 0.088 | | 0.017 | 0.093 | |
| | [0.058] | [0.080] | | [0.069] | [0.094] | | [0.011] | [0.019] | | [0.013] | [0.022] | |
| ***D-D*** | -0.454 *** | | | -0.412 *** | | | 0.075 *** | | | 0.076 *** | | |
| | [0.114] | | | [0.136] | | | [0.025] | | | [0.028] | | |
| **Observations** | 3,653 | | | 1,954 | | | 3,653 | | | 1,954 | | |

*Notes*: Robust standard errors, clustered at the municipality level, are presented in square brackets. The symbols ***, (**) and [*] stand for significance at the 1%, (5%) and [10%] levels, respectively. Approximately 15% of the total number of households represents the experimental group. See text for definitions of outcomes, experimental and non experimental households and before and after years.

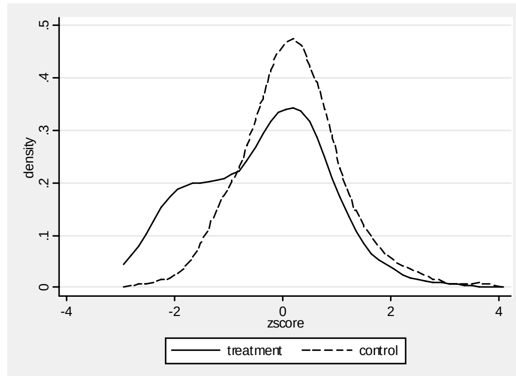
**Figure 1. Z-score Weight-for Height Densities**
**(Children between 0 and 4 years of age)**

**Treatment Children vs. Control Children**

**1998**

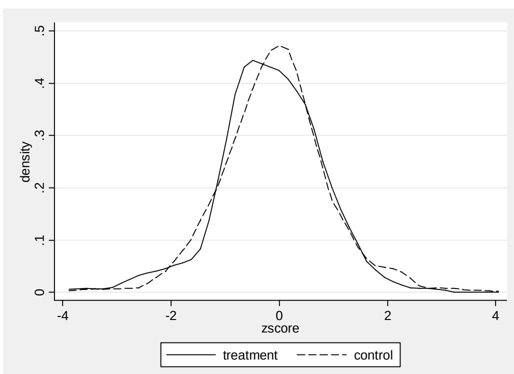



**2001**

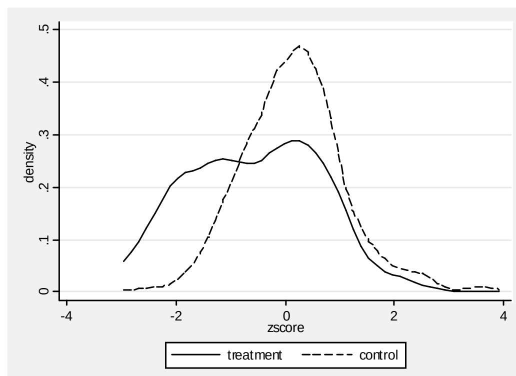



**Treatment Children vs. Control Children (Boys)**

**1998**

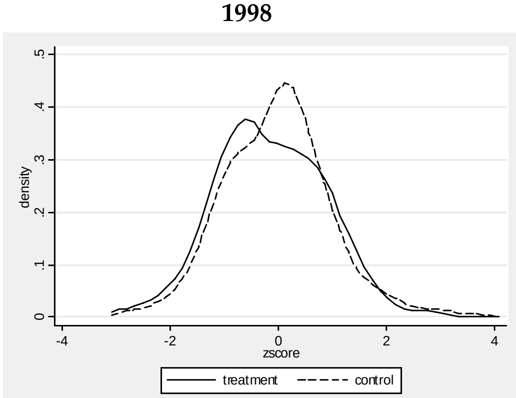



**2001**




**Treatment Children vs. Control Children (Girls)**

**1998**




**2001**

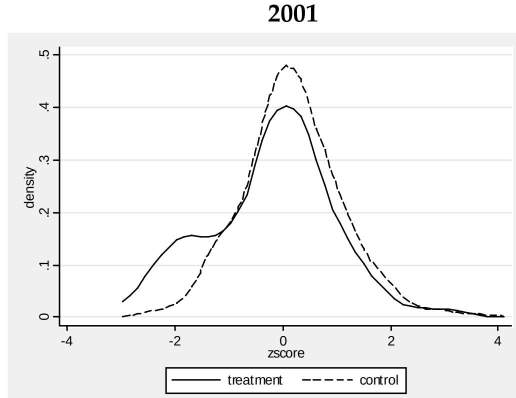


**Table 5. Difference-in-Difference Models of the Impact of the Shock on Investments in Children (Multivariate Reduced Form Estimates)**

| | Total Sample | | | | | |
|---|---|---|---|---|---|---|
| | LPM Pooled | | | Probit Pooled | | |
| Outcome | (i) | (ii) | N | (i) | (ii) | N |
| School attendance (children between 6 and 15 years of age) | 0.028<br>[0.025] | 0.025<br>[0.026] | 6,653 | 0.024<br>[0.021] | 0.024<br>[0.021] | 6,653 |
| Child labor force participation (children between 6 and 15 years of age) | 0.121 ***<br>[0.020] | 0.113 ***<br>[0.028] | 7,503 | 0.100 ***<br>[0.034] | 0.085 ***<br>[0.031] | 7,503 |
| Joint school attendance and child labor force participation | 0.104 ***<br>[0.026] | 0.107 ***<br>[0.026] | 6,653 | 0.084 ***<br>[0.033] | 0.086 ***<br>[0.033] | 6,653 |
| Health care utilization, conditioned on being sick (children between 0 and 6 years) | -0.173 *<br>[0.092] | -0.183 *<br>[0.103] | 1,035 | -0.181 *<br>[0.093] | -0.207 *<br>[0.108] | 1,035 |
| Health care utilization, conditioned on being sick (children between 6 and 15) | -0.110 ***<br>[0.038] | -0.086 **<br>[0.040] | 2,950 | -0.106 ***<br>[0.036] | -0.087 *<br>[0.042] | 2,950 |
| Z-score weight-for-height (children between 0 and 4 years of age) | -0.466 ***<br>[0.179] | -0.501 ***<br>[0.192] | 2,020 | ---- | ---- | 2,020 |
| Children with severe undernutrition (<-2 Z) (children between 0 and 4 years of age) | 0.070 **<br>[0.033] | 0.073 **<br>[0.037] | 2,020 | 0.084 ***<br>[0.040] | 0.087 ***<br>[0.049] | 2,020 |
| Household and individual demographics | yes | yes | | yes | yes | |
| Controls for local public investment | no | yes | | no | yes | |
| Controls for municipality effects | no | yes | | no | yes | |

| | Rural Sample | | | | | |
|---|---|---|---|---|---|---|
| | LPM Pooled | | | Probit Pooled | | |
| Outcome | (i) | (ii) | N | (i) | (ii) | N |
| School attendance (children between 6 and 15 years of age) | 0.034<br>[0.035] | 0.026<br>[0.037] | 3,221 | 0.042<br>[0.037] | 0.035<br>[0.041] | 3,221 |
| Child labor force participation (children between 6 and 15 years of age) | 0.092 **<br>[0.038] | 0.084 **<br>[0.037] | 3,784 | 0.100 **<br>[0.048] | 0.084 **<br>[0.046] | 3,784 |
| Joint school attendance and child labor force participation | 0.087 **<br>[0.035] | 0.093 ***<br>[0.035] | 3,221 | 0.080 **<br>[0.045] | 0.086 **<br>[0.047] | 3,221 |
| Health care utilization, conditioned on being sick (children between 0 and 6 years) | -0.227 **<br>[0.099] | -0.197<br>[0.125] | 618 | -0.230 **<br>[0.091] | -0.228 *<br>[0.122] | 618 |
| Health care utilization, conditioned on being sick (children between 6 and 15) | -0.112 **<br>[0.049] | -0.099 *<br>[0.053] | 1,520 | -0.102 **<br>[0.044] | -0.094 *<br>[0.052] | 1,487 |
| Z-score weight-for-height (children between 0 and 4 years of age) | -0.493 **<br>[0.206] | -0.493 **<br>[0.228] | 1,190 | ---- | ---- | |
| Children with severe undernutrition (<-2 Z) (children between 0 and 4 years of age) | 0.072 **<br>0.033 | 0.071 *<br>[0.039] | 1,190 | 0.086 ***<br>[0.045] | 0.086 ***<br>[0.046] | 1,190 |
| Household and individual demographics | yes | yes | | yes | yes | |
| Controls for local public investment | no | yes | | no | yes | |
| Controls for municipality effects | no | yes | | no | yes | |

*Notes*: Robust standard errors clustered at the municipality level are presented in square brackets. Probit coefficients reported correspond to marginal effects. The symbols ***, (**) and [*] stand for significance at the 1%, (5%) and [10%] levels, respectively. The analysis here includes only households with at least one child under the age of 15. Pre-shock household and individual demographics include child's age (in months for models of nutritional status), gender and school attainment, parental education, gender of the household head, number of members within the household, log of income per capita and area of location. Other pre-shock controls include dummies to identify households owning businesses and land to crop. Dummies of pre-shock programs of social investment at the community level include public assistance to construct/improve schools, health centers, housing, provision of water, sewage, electricity or start programs to promote employment, health and donation of food and drugs. Approximately 15% of the total number households represent the experimental group. See text for definitions of outcomes, experimental and non experimental households and before and after years.

**Table 6. Difference-in-Difference Reduced Form Estimates of the Impact of the Shock on Investments in Children (Experimental Samples Defined by Main Type of Pre-shock Crop Cultivated)**

| Outcomes | Corn | | | | Beans | | | | Rice | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Raw Diff-in-diff | OLS | Probit | N | Raw Diff-in-diff | OLS | Probit | N | Raw Diff-in-diff | OLS | Probit | N |
| School attendance (children between 6 and 15 years of age) | -0.003 | -0.048 | -0.056 | 1,427 | 0.294 | 0.192 | 0.205 | 150 | 0.214 | 0.297 | 0.206 | 157 |
| | [0.072] | [0.079] | [0.092] | | [0.193] | [0.292] | [0.160] | | [0.187] | [0.232] | [0.108] | |
| Child labor force participation (children between 6 and 15 years of age) | 0.069 | 0.124 * | 0.184 ** | 1,427 | 0.284 ** | 0.381 * | 0.458 ** | 150 | 0.066 | 0.134 | 0.221 * | 157 |
| | [0.057] | [0.071] | [0.105] | | [0.140] | [0.195] | [0.315] | | [0.097] | [0.114] | [0.212] | |
| Joint school attendance and child labor participation | 0.021 | 0.011 | 0.011 | 1,427 | 0.244 | 0.203 | 0.201 | 150 | 0.182 * | 0.288 ** | 0.331 *** | 157 |
| | [0.053] | [0.063] | [0.057] | | [0.195] | [0.244] | [0.305] | | [0.088] | [0.092] | [0.192] | |
| Z-score weight-for-height (children between 0 and 4 years of age) | -0.308 | -0.242 | --- | 536 | -0.909 *** | -1.177 ** | --- | 70 | -1.015 ** | -0.624 | --- | 54 |
| | [0.301] | [0.361] | | | [0.339] | [0.410] | | | [0.486] | [0.369] | | |
| Children with severe undernutrition (<-2 Z) (children between 0 and 4 years of age) | 0.084 * | 0.062 | 0.060 | 536 | 0.314 | --- | --- | 70 | 0.078 | 0.166 | --- | 54 |
| | [0.049] | [0.063] | [0.060] | | [0.200] | | | | [0.052] | [0.204] | | |

*Notes*: Robust standard errors clustered at the municipality level are presented in square brackets. Probit coefficients reported correspond to marginal effects. The symbols ***, (**) and [*] stand for significance at the 1%, (5%) and [10%] levels, respectively. Sub-samples used here include only children under the age of 15 in rural areas. Pre-shock household and individual demographics include child's age (in months for models of nutritional status), gender and school attainment, parental education, gender of the household head, number of members within the household, log of income per capita and area of location. Other pre-shock controls include dummies to identify households owning businesses and land to crop. Dummies of pre-shock programs of social investment at the community level include public assistance to construct/improve schools, health centers, housing, provision of water, sewage, electricity or start programs to promote employment, health and donation of food and drugs. Approximately 15% of the total number households represent the experimental group. See text for definitions of outcomes, experimental and non experimental households on the basis of pre-shock crops cultivated and before and after years.

**Table 7. Difference-in-Difference Propensity Score Matching Estimates of the Impact of the Shock on Investments in Children (Reduced Form Estimates)**

| Outcome | Type of Kernel [a] NN(10) bw = 0.01 | G bw = 0.01 | E bw = 0.01 | LL bw = 0.01 | *N* | *CS* |
|---|---|---|---|---|---|---|
| School attendance (children between 6 and 15 years of age) | 0.056<br>[0.057] | 0.052<br>[0.054] | 0.047<br>[0.056] | 0.064<br>[0.060] | 1,641 | 99.1% |
| Child labor force participation (children between 6 and 15 years of age) | 0.094 ***<br>[0.035] | 0.091 ***<br>[0.034] | 0.085 **<br>[0.034] | 0.094 **<br>[0.037] | 1,641 | 99.1% |
| Joint school attendance and child labor force participation | 0.086 ***<br>[0.030] | 0.080 ***<br>[0.028] | 0.075 ***<br>[0.029] | 0.085 ***<br>[0.033] | 1,641 | 99.1% |
| Health care utilization, conditioned on being sick (children between 0 and 6 years) | -0.146<br>[0.096] | -0.025<br>[0.115] | -0.175<br>[0.123] | ---- | 122 | 96.9% |
| Health care utilization, conditioned on being sick (children between 6 and 15) | -0.016<br>[0.056] | -0.066<br>[0.068] | -0.140 *<br>[0.075] | ---- | 124 | 97.4% |
| Z-score weight-for-height (children between 0 and 4 years of age) | -0.218 **<br>[0.098] | -0.251 **<br>[0.096] | -0.243 **<br>[0.098] | -0.234 **<br>[0.099] | 681 | 100% |
| Children with severe undernutrition (<-2 Z) (children between 0 and 4 years of age) | 0.101 ***<br>[0.028] | 0.099 ***<br>[0.028] | 0.102 ***<br>[0.028] | 0.098 ***<br>[0.032] | 681 | 100% |

*Notes*: Bootstrapped standard errors presented in square brackets were obtained from 500 replications. The symbols ***, (**) and [*] stand for significance at the 1%, (5%) and [10%] levels, respectively. The analysis here includes only households with at least one child under the age of 15. Units matched on the propensity score from a logistic regression on presence in the treatment group. Pre-shock household covariates in the logistic regression include area of location (urban or rural), municipality codes, log of income per capita, parental education, distance to closest school and closest health center and a set of dummies to identify households owning a dwelling, businesses and land to crop. Results presented in this table are very similar to those obtained with bandwidths ranging from 0.005 to 0.025. Approximately 15% of the total number households represent the experimental group. See text for definitions of outcomes, experimental and non experimental households and before and after years.

[a] NN(10) = 10 nearest neighbors; G = Gaussian; E = Epanechnikov; LL = local linear; bw = bandwith; CS = common support.

## Table 8. Pre-Shock Covariates Trends and Results from Pre-shock Difference-in-Difference Models

| Covariates | Total sample: 1998-1993 Diff-in-diff | Total sample: 1993 Treated (Mitch=1) | Total sample: 1993 Control (Mitch=0) | N | Rural sample: 1998-1993 Diff-in-diff | Rural sample: 1993 Treated (Mitch=1) | Rural sample: 1993 Control (Mitch=0) | N |
|---|---|---|---|---|---|---|---|---|
| Number of members per household | 0.27 | 6.94 | 6.95 | 7,556 | 0.000 | 7.32 | 7.32 | 3,103 |
| | [0.391] | [0.035] | [0.024] | | [0.408] | [0.054] | [0.039] | |
| Number of children per household | 0.01 | 2.62 | 2.62 | 7,556 | 0.07 | 3.06 | 3.05 | 3,103 |
| | [0.101] | [0.057] | [0.038] | | [0.172] | [0.098] | [0.066] | |
| Proportion of children that are girls | 0.023 | 0.483 | 0.489 | 6,316 | -0.024 | 0.508 | 0.482 | 2,665 |
| | [0.017] | [0.010] | [0.006] | | [0.028] | [0.015] | [0.010] | |
| Age of household head | 0.75 | 41.81 | 42.19 | 6,328 | 3.656 ** | 41.57 | 42.47 | 2,668 |
| | [0.776] | [0.420] | [0.286] | | [1.422] | [0.670] | [0.458] | |
| Age of children | 0.19 | 7.10 | 7.14 | 6,316 | 0.805 ** | 6.69 | 6.95 | 6,316 |
| | [0.237] | [0.109] | [0.073] | | [0.290] | [0.163] | [0.109] | |
| Years of schooling: head of household | -0.07 | 6.19 | 6.31 | 4,927 | 0.24 | 4.17 | 4.44 | 1,765 |
| | [0.447] | [0.156] | [0.101] | | [0.330] | [0.225] | [0.154] | |
| Female headed households | 0.047 | 0.257 | 0.290 | 6,328 | 0.036 | 0.174 | 0.200 | 2,668 |
| | [0.028] | [0.013] | [0.009] | | [0.447] | [0.017] | [0.012] | |
| Monthly income per capita | -1,197 | 2,972 | 3,073 | 6,302 | -22.70 | 1,141 | 1,155 | 2,660 |
| | [1181.3] | [446.1] | [335.4] | | [540.4] | [141.4] | [80.77] | |
| Percent with own house | -0.057 | 0.573 | 0.533 | 6,324 | -0.054 | 0.510 | 0.472 | 2,666 |
| | [0.038] | [0.014] | [0.010] | | [0.040] | [0.023] | [0.015] | |
| Distance to closest health center | 3.617 ** | 18.32 | 20.84 | 6,328 | 8.488 *** | 25.36 | 30.62 | 2,668 |
| (minutes) | [1.760] | [0.787] | [0.540] | | [3.052] | [1.715] | [1.195] | |
| Distance to closest primary school | 3.115 * | 12.96 | 14.89 | 6,328 | 4.892 *** | 12.83 | 15.34 | 2,668 |
| (minutes) | [1.629] | [0.255] | [0.198] | | [1.835] | [0.495] | [0.387] | |

| Outcomes | Total sample: Raw D-D | Total sample: OLS Pooled | Total sample: Probit Pooled | N | Rural sample: Raw D-D | Rural sample: OLS Pooled | Rural sample: Probit Pooled | N |
|---|---|---|---|---|---|---|---|---|
| School attendance (children between 6 and 15 years of age) | -0.014 | 0.037 | -0.001 | 7,603 | 0.031 | 0.064 | 0.026 | 2,761 |
| | [0.033] | [0.036] | [0.029] | | [0.052] | [0.054] | [0.082] | |
| Child labor participation (children between 6 and 15 years of age) | 0.021 | -0.013 | 0.000 | 7,603 | 0.000 | -0.053 | -0.032 | 2,761 |
| | [0.021] | [0.028] | [0.020] | | [0.031] | [0.039] | [0.035] | |
| Joint school attendance and child labor participation | 0.014 | 0.010 | 0.018 | 7,603 | -0.009 | -0.025 | -0.014 | 2,761 |
| | [0.013] | [0.013] | [0.014] | | [0.022] | [0.022] | [0.020] | |
| Health care utilization, conditioned on being sick (children between 6 and 15) | -0.012 | -0.012 | -0.009 | 1,325 | 0.061 | 0.149 | 0.141 | 633 |
| | [0.052] | [0.060] | [0.061] | | [0.065] | [0.123] | [0.113] | |
| Health care utilization, conditioned on being sick (children between 0 and 6 years) | -0.049 | -0.136 | -0.178 | 203 | 0.075 | -0.204 | -0.135 | 122 |
| | [0.053] | [0.138] | [0.129] | | [0.065] | [0.235] | [0.211] | |
| Z-score weight-for-height (children between 0 and 4 years of age) | -0.084 | 0.022 | --- | 2,078 | -0.078 | -0.212 | --- | 990 |
| | [0.067] | [0.102] | | | [0.101] | [0.132] | | |
| Children with severe undernutrition (<-2 Z) (children between 0 and 4 years of age) | 0.007 | -0.009 | -0.007 | 2,078 | 0.026 | -0.013 | -0.021 | 990 |
| | [0.013] | [0.013] | [0.013] | | [0.019] | [0.035] | [0.030] | |

*Notes*: Robust standard errors clustered at the municipality level are presented in square brackets. Probit coefficients reported correspond to marginal effects. The symbols ***, (**) and [*] stand for significance at the 1, (5%) and [10%] levels, respectively. The unit of analysis for the first panel (covariates) is a household with at least one child under the age of 15. The unit of analysis for the second panel (outcomes) is a child within the age ranges defined in the table. Several specifications run included household and individual demographics such as age in years (in months for models of nutritional status), gender of the child, number of members within the household, parental school attainment, gender of the household head, log of income per capita. Other controls include dummies of households owning land to crop, distance to closest health center and closest school and area of location. See text for definitions of outcomes, experimental and non experimental households and before and after years.

**Table 9. Difference-in-Difference-in-Difference Models of the Impact of the Shock on Investments in Children in Rural Households (Multivariate Reduced Form Estimates)**

| Outcome | Raw D-D | OLS Pooled | Probit Pooled | *N* |
|---|---|---|---|---|
| School attendance (children between 6 and 15 years of age) | 0.020<br>[0.079] | -0.059<br>[0.062] | 0.003<br>[0.094] | 5,679 |
| Child labor force participation (children between 6 and 15 years of age) | 0.055<br>[0.046] | 0.147 ***<br>[0.055] | 0.136 *<br>[0.100] | 6,154 |
| Joint school attendance and child labor force participation | 0.076 **<br>[0.038] | 0.100 **<br>[0.048] | 0.081 *<br>[0.075] | 5,679 |
| Health care utilization, conditioned on being sick (children between 0 and 6 years) | -0.298 **<br>[0.137] | -0.061<br>[0.196] | 0.014<br>[0.276] | 813 |
| Health care utilization, conditioned on being sick (children between 6 and 15) | -0.158 *<br>[0.084] | -0.189 **<br>[0.083] | -0.113 *<br>[0.063] | 2,199 |
| Z-score weight-for-height (children between 0 and 4 years of age) | -0.334 *<br>[0.191] | -0.391 *<br>[0.217] | -- | 2,716 |
| Children with severe undernutrition (<-2 Z) (children between 0 and 4 years of age) | 0.048<br>[0.033] | 0.076 **<br>[0.037] | 0.128 **<br>[0.100] | 2,716 |

*Notes:* Robust standard errors clustered at the municipality level are presented in square brackets. Probit coefficients reported correspond to marginal effects. The symbols ***, (**) and [*] stand for significance at the 1%, (5%) and [10%] levels, respectively. The analysis here includes only households with at least one child under the age of 15. Pre-shock household and individual demographics include child's age (in months for models of nutritional status), gender and school attainment, parental education, gender of the household head, number of members within the household, log of income per capita and area of location. Other pre-shock controls include dummies to identify households owning land to crop. See text for definitions of outcomes, experimental and non experimental households and before and after years. See also test for assumptions used to construct the panels in the two periods of analysis (1993-1998 and 1998-2001).

**Table 10. Difference-in-Difference Estimates of Adult Consumption and Adult Nutritional Status in Rural Households (Simple and Multivariate Reduced Form Estimates)**

| Outcome | Pre-shock mean | | Raw | OLS | *N* |
|---|---|---|---|---|---|
| | Treatment (Mitch=1) | Control (Mitch=0) | D-D | Pooled | |
| Monthly Consumption Share: Alcohol | 0.207 | 0.292 | -0.099 | -0.024 | 2,097 |
| | [0.072] | [0.056] | [0.163] | [0.160] | |
| Monthly Consumption Share: Tobacco | 0.566 | 0.511 | 0.040 | 0.201 | 2,097 |
| | [0.105] | [0.041] | [0.230] | [0.197] | |
| Body Mass Index | 27.40 | 28.83 | 0.028 | 0.035 | 5,186 |
| | [0.271] | [0.249] | [0.443] | [0.382] | |
| Weight/Height - Percentage of Reference | 161.99 | 176.63 | 0.876 | 1.220 | 5,186 |
| Median WHO | [3.091] | [2.848] | [3.678] | [3.499] | |

*Notes*: Robust standard errors clustered at the municipality level presented in square brackets. The units of analysis for the first two outcomes are households with at least one child under the age of 15. Monthly consumption shares of alcohol and tobacco calculated as the ratio of monthly expenditure on these items to total monthly consumption per capita at the household level. Both shares were adjusted for differences in geographic prices. Pre-shock demographic covariates in extended models of consumption shares included number of children, characteristics of the household head (age, sex and schooling) and dummies to identify single-headed households. Other pre-shock controls included were the log of income per capita and dummies to identify households owning businesses. Models of anthropometric outcomes estimated from a pseudo-panel at the municipality level between 1998 and 2001. The units of analysis for these models were women with the following characteristics: wife, head of the household or grand mother, with ages between 18 and 49 years, no pregnant and living in households with at least one child under the age of 15. Pre-shock demographic covariates in extended models of anthropometric measures included total number of births and number of household members, women's age and schooling. Other pre-shock controls included a wealth index from principal component scores and dummies to identify single-headed households. See text for definitions of outcomes, experimental and non experimental households and before and after years, and for assumptions used to construct the pseudo-panel for the period 1998-2001.