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Abstract

After catastrophes, international donors offering assistance must decide whether to channel their resources via the local government or non-governmental organizations (NGOs). We examine how these channels differ in the timing, locations, and populations that they assist by combining data on aid received by Nicaraguan households over ten years with municipal election results and an exogenous measure of a catastrophe (Hurricane Mitch). In the short term (0-3 years post), NGOs provided aid according to hurricane severity with no evidence of political influence, while government aid allocations were unrelated to hurricane severity. Instead, the evidence suggests that short-term government aid was distributed along political lines, though in a nuanced way. The catastrophe also had long-term effects on aid, with households in the disaster area receiving significantly more aid than households in other areas—from both NGOs and the government—in the period 3 to 7 years after the hurricane.

Keywords: development aid, non-governmental organizations, climate change, hurricane, Nicaragua

JEL classification: Q01, Q54, O12

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After a disaster, who gets help? Populations in developing countries are increasingly concentrating in vulnerable areas and extreme weather events are predicted to increase in severity (Freeman, Keen and Mani, 2003; Pachauri and Reisinger, 2007; Solomon et al., 2007). Thus, the distribution of disaster aid will have increasingly large consequences. This paper presents evidence that who receives aid after a disaster depends on who delivers the aid. International donors that attempt to provide assistance to disaster areas must choose whether to channel resources through the local government or via non-governmental entities. This analysis reports how these two channels—local government and non-governmental organizations (NGOs)—differed in the populations that they assisted, at a household level, after the deadliest Atlantic hurricane in two centuries.[1]

National-level studies of NGO aid allocations show remarkable similarities in the destinations of NGO- and government-provided aid (Dreher, Mölders and Nunnenkamp, 2010; Keck, 2014; Koch et al., 2009; Nunnenkamp and Öhler, 2011; Nunnenkamp, Weingarth and Weisser, 2009). However, empirical evidence concerning the distribution of this aid *within* a disaster area is scarce. The existing evidence is limited to relatively small events (e.g., Francken, Minten and Swinnen, 2012; Takasaki, 2011), lacks measures of disaster severity (e.g., Aldrich, 2010; Nose, 2014), or considers data that reflects at most one year following the disaster in question (e.g., Francken, Minten and Swinnen, 2012; Morris and Wodon, 2003; Takasaki, 2011). This paper builds on the existing literature by examining micro-level data that span from before a catastrophic disaster to seven years after the event, and by using an objective measure of the geographical variation in the disaster's impact.

While a focus on aid allocations at the micro-level precludes an analysis across countries and disasters (because comparable data are not available), the context considered here—Nicaragua and Hurricane Mitch—is particularly relevant. Climate scientists predict that higher temperatures, in both the atmosphere and ocean surface waters, will increase the likelihood of extremely severe tropical cyclones (Knutson et al., 2010; Pachauri and Reisinger,

[1] This method of using a catastrophic shock to study the political economy of aid is similar in spirit to Besley and Case (1995), who use natural disasters to study the effects of term limits on government responsiveness.

2007; Scheraga et al., 2003; Solomon et al., 2007).[2] Specific predictions include "substantial increases in the frequency of the most intense cyclones" and "increases of the order of twenty percent in the precipitation rate within 100km of the storm center" (Knutson et al., 2010). Furthermore, the regions of the world historically affected by these storms include many poorer, less-developed nations, like Nicaragua, and populations in these regions are increasingly concentrating in areas that are vulnerable to climate-related disasters (Freeman, Keen and Mani, 2003; Knutson et al., 2010).

Hurricane Mitch may have looked like an outlier at the time it struck (in late October of 1998), but it is representative of the levels of severity that storms are predicted to achieve with greater frequency in the future. Mitch caused more than five times as many deaths as Hurricane Katrina in the U.S., with total damages estimated in excess of $7 billion (2015 USD) (Knabb, Rhome and Brown, 2005; McCown et al., 1999). The storm dropped as much as 50 inches of rain in some parts of Nicaragua, leaving an estimated twenty percent of the Nicaraguan population without habitable dwellings and destroying 1500 miles of roads, 300 schools, 90 health clinics, and one-third of the country's agricultural crops (World Bank, 2001). After the storm cleared, an immediate donation of supplies was airlifted from Mexico to Nicaragua, while many other countries provided additional supplies and financial donations approaching $500 million.[3]

In Nicaragua, efforts to deliver this assistance to the victims were caught in a political fight. The major opposition party, the *Frente Sandinista de Liberación Nacional*, accused the ruling coalition of giving aid only to their own supporters. Nicaraguan President Arnoldo Alemán, of the ruling *Partido Liberal Constitucionalista* (PLC), countered with accusations that the Sandinistas were distorting the facts in order to capture the country's resources. He also proposed to tax the incoming aid.[4]

[2] The term "tropical cyclone" refers to the broad class of weather phenomena that includes Atlantic hurricanes, typhoons (as hurricanes are called in the west Pacific), and less severe (measured by windspeed) tropical storms.

[3] The largest donors included Spain ($154 million), Sweden ($146 million, pledged over three years), and the U.S. ($117 million)) (McCown et al., 1999).

[4] Some Nicaraguans referred to Alemán as "El que llegó y se fué" ("he who came and left"), in reference to how quickly he departed the devastated areas without offering help (Olson et al., 2001).

While the details of the present study are particular to Nicaragua, similar claims of politically manipulated disaster aid allocations have emerged elsewhere. For example, reports of politicians campaigning with resources intended for the victims surfaced only weeks after Typhoon Haiyan struck the Philippines in 2013.[5] Whether longer-term, post-Haiyan reconstruction efforts are influenced by political affiliations remains to be seen.

Following catastrophic storms, where does the aid flow? The primary challenge to retrieving estimates of the causal effect of a natural disaster on aid allocations is the limited availability of appropriate data, and an important feature of the setting studied here is the unusual wealth of available data. While previous studies are limited to data on aid allocations during the twelve months after a storm, the data available for Nicaragua reflect three different time-periods corresponding approximately to the four years before the storm, the three years immediately following it, and the four years after that. It is perhaps surprising that a disaster might affect the distribution of aid for more than three years after the event, yet Anttila-Hughes and Hsiang (2012) show that typhoons in the Philippines cause long-term harmful effects on a variety of outcomes (including infant mortality and unearned income) that exceed the immediate damages by a magnitude of fifteen to one. Whether these longer-term damages translate into longer-term effects on aid allocations is a question that the present paper helps to answer.

The empirical approach of using a natural disaster as an exogenous source of identifying variation is similar in spirit to analyses that use precipitation or other weather variables (see, e.g., Besley and Case, 1995). A second challenge to the identification of the causal effects of a hurricane on aid allocations, which is common to analyses of weather variables but left largely unaddressed in the existing literature on disasters, is the possibility that a disaster's impact might be correlated with some unobserved factor that determines the outcome of interest. A simple mechanism by which this might arise, in the context of development aid, is the (potential) correlation of the impacts of disasters over time. For example, the impacts

[5] See *Are Philippine Politicians Using Typhoon Aid to Their Advantage?*, CNN, Nov 22, 2013, at http://www.cnn.com/2013/11/22/world/asia/philippines-politicians-typhoon-aid-advantage-irpt/

of earlier storms could affect prior aid allocations, or economic development, which could in turn affect subsequent allocations of aid. In Section C, we present evidence that the historical impact of hurricanes in Nicaragua follows no systematic pattern and is therefore unlikely to be correlated with unobservable characteristics that might bias estimates of the effect of hurricane impact on the probability that a household receives aid.

The existence of data covering multiple time periods—and the fortuitous timing of data collection relative to the hurricane's impact—also allows for an examination of whether the event is appropriately understood as a natural experiment. The data collected before the hurricane reveal that patterns in the allocations of aid after the disaster are not merely reflective of pre-storm patterns in the distribution of aid.

A third concern is that measures of disaster damage may be endogenous to aid allocations. Indications of a disaster's impact that are made by government officials are subject to political manipulation, while measures of disaster damage constructed from survey reports could potentially be misrepresented by individuals attempting to attract aid. We eliminate the potential for these factors to influence the measurement of the hurricane's impact by constructing an exogenous measure based on independent scientific data on precipitation.[6]

This analysis yields two important findings that, in addition to the methodological improvements described above, expand the evidence on the household-level distribution of aid following natural disasters. First, we find that effects of Hurricane Mitch on aid allocations by both NGOs and the local government extend as long as three to seven years after the event—much longer than any effects identified in the existing literature. Second, we find that aid from the government was heavily influenced by political affiliations in the three years immediately following the hurricane. The evidence strongly suggests that, in the parts of Nicaragua that experienced less than the average hurricane impact, households in areas controlled by the opposition party were about 20 percent percent less likely to receive assis-

[6] While other forces during a hurricane, such as strong winds, can also cause damage, reports of damage from Hurricane Mitch and other hurricanes that have affected Nicaragua point most frequently to precipitation and the subsequent flooding and landslides as the main cause (Hellin, Haigh and Marks, 1999).

tance than households in areas controlled by the ruling party.[7] Furthermore, governmental assistance during this time was *not* provided according to the precipitation-based measure of the hurricane's impact. On the other hand, there is no evidence of political influence on assistance provided by NGOs, who were more likely to assist households that experienced larger impacts in both the short and long term.

The rest of the paper proceeds as follows. Section I describes the relevant findings from the literature on the political economy of disaster aid, and Section II discusses some important features of the political situation in Nicaragua around the time of Hurricane Mitch. The empirical approach for estimating the effect of the hurricane on the probability that a household receives aid is laid out in Section III. The data used in the analysis are described in Section IV, including a description of the construction of the precipitation-based measure of hurricane impact and an analysis of the historical impact of hurricanes in Nicaragua (in Section C). Section V presents and discusses the estimated relationships between the hurricane's impact and the aid allocations made by the Nicaraguan government and NGOs, and Section VI offers concluding remarks.

I Major Channels for Providing Disaster Aid

A large literature studies the political economy of disaster aid allocations at a national level. Like the evidence regarding foreign aid in general (e.g., Alesina and Dollar, 2000), much of the evidence suggests that country-to-country flows of post-disaster aid are subject to political influence and strategic considerations. Common cultural ties, such has a shared language or colonial history, increase the probability that one country will aid another in the wake of a disaster (Eisensee and Strömberg, 2007). Additionally, Drury, Olson and Belle (2005) find that foreign policy and domestic factors are the "overriding determinant" of disaster aid allocations made by the US government. The evidence is not in complete agree-

[7] In the least-affected parts of Nicaragua, households in opposition controlled municipalities were 26 percent less likely to receive aid than those in areas controlled by the ruling party. In areas that experienced the average impact, the corresponding difference was 11 percent.

ment, however, as Becerra, Cavallo and Noy (2014) find no evidence of political or strategic influences across 196 countries and 39 years worth of aid flows and disasters. Becerra, Cavallo and Noy (2014) also point out that official post-disaster aid typically amounts to only three percent of estimated damage from a disaster, even for very large disasters that receive substantial attention from the media.

Studies on the determinants of aid allocations by NGOs, just like the evidence on government aid, are largely limited to national-level estimates. Peter Nunnenkamp, Axel Dreher, and coauthors use data on Official Development Assistance (ODA) from several European countries to consider the so-called "article of faith" (Tendler, 1982) that NGOs are "closer" to the people they serve and therefore better at targeting aid according to need (Dreher, Mölders and Nunnenkamp, 2010; Koch et al., 2009; Nunnenkamp and Öhler, 2011; Nunnenkamp, Weingarth and Weisser, 2009). The evidence in these studies consistently finds that NGOs are very similar to national governments and, at a national level, "replicate the location choices" (Koch et al., 2009) of governmental destinations of ODA. They also find that NGOs tend to follow each other and cluster their activities in the same countries. Evidence from the U.S. is similar, with aid from US-based NGOs "mirroring" ODA allocations from the U.S. government (Keck, 2014).

Contrary to the similarities revealed by these national-level analyses of aid, we find clear differences in how NGOs and the government allocated aid in response to Hurricane Mitch. This finding, derived from more extensive data than has been considered previously, is the central contribution of this paper. To date, evidence concerning the effects of natural disasters on the household-level distribution of aid is surprisingly rare, and existing studies have not had pre-disaster data for comparison or considered data on longer-term (beyond twelve months) allocations of aid (e.g., Francken, Minten and Swinnen, 2012; Morris and Wodon, 2003; Takasaki, 2011, 2014).[8]

[8] As of September 2015, a search for "disaster aid" on EconLit reveals only four studies that regress some measure of aid received by households or individuals on a measure of disaster damage (Francken, Minten and Swinnen, 2012; Morris and Wodon, 2003; Takasaki, 2011, 2014), and two others that study post-disaster aid allocations but do not include a measure of disaster damage (Aldrich, 2010; Nose, 2014).

In the work most similar to the analysis described here, Francken, Minten and Swinnen (2012) consider the distribution of relief aid separately by NGOs and local government in the eight months after Cyclone Gafilo struck Madagascar in 2004. As in other studies, the absence of data on patterns of aid allocations prior to the disaster makes it is difficult to know if their estimates reveal changes in resource allocations that are due to the disaster, or whether they simply reflect pre-existing patterns amplified by a surge in the availability of aid. Nonetheless, Francken, Minten and Swinnen (2012) find evidence that suggests political manipulation: among the areas that the government claimed were affected by the cyclone, aid from the government was more likely to go to communities with greater support for the president. On the other hand, NGO aid was not influenced by presidential support.

Several other studies reveal patterns that suggest political manipulation of aid, but do not report results separately for NGO- and government-provided aid. Takasaki (2011) reports that village elites received assistance before other groups after a cyclone in Fiji, though they did not receive greater total amounts of aid. Nose (2014) finds that stronger social ties among fishermen in Indonesia were associated with a higher probability of receiving aid after the 2004 tsunami in the Indian Ocean. Studying the same event, Aldrich (2010) finds that villages comprised of more members from lower castes in India were less likely to receive aid. Aldrich (2010) and Francken, Minten and Swinnen (2012) also report positive correlations between wealth and the receipt of post-disaster aid, though Morris and Wodon (2003) find no relationship between wealth and post-hurricane aid in Honduras six to nine months after Hurricane Mitch.

II Nicaragua and Hurricane Mitch

Nicaragua is the second poorest country in the western hemisphere and its recent political history has been contentious.[9] At the time of Hurricane Mitch, GDP per capita was around

[9]The longer history has been contentious as well. The primary left wing political party, the *Frente Sandinista de Liberación Nacional*, grew out of opposition to the military dictatorship that was in control of Nicaragua in the 1960s. A devastating earthquake in 1972, combined with general unrest and dissatisfaction with the concentration and control of wealth by the regime

$1,000 (2015 USD) and the literacy rate was 60 percent (CIA, 2013; ECLAC, 1999; World Bank, 2014).

For eight years on either side of Hurricane Mitch (1990-2006), Nicaragua's national elections were won by the center-right political coalition led by the *Partido Liberal Constitucionalista* (PLC). At the time of Hurricane Mitch, the PLC controlled the presidency and national assembly, although 51 out of 143 total *alcaldes*, the locally elected municipal leaders, were affiliated with the opposition *Sandinistas*. Despite corruption charges in 2000 against some of the party's leaders, PLC candidate Enrique Bolaños won the presidential election in 2001 and the PLC retained a majority of the seats in the National Assembly. In 2006, the Sandinistas regained control of both the presidency, with the election of Daniel Ortega, and the National Assembly. The contentious nature of politics in Nicaragua has continued, and the transparency and legitimacy of elections have been called into question by international observers, who were banned from monitoring the 2008 elections.

Central America in general, and Nicaragua in particular, is susceptible to frequent hurricanes. Fourteen hurricanes passed within 200 miles of Nicaragua's borders between 1960 and 2010, though Mitch was unique in the extent of the damage it caused. Mitch made landfall on October 26, 1998, just north of the border between Nicaragua and Honduras.[10] With maximum sustained winds of 180 miles per hour, Mitch moved inland and dropped as much as fifty inches of rain in some parts of Nicaragua. The hurricane caused an estimated 11,000 total deaths (3,800 in Nicaragua), vastly more than those caused by other storms that have affected the region.[11]

This paper is the first to study the political economy of the aid response to Hurricane

in power, led to an outpouring of support for the Sandinistas and a subsequent uprising (Black, 1981) and the Sandinistas took control of national politics from 1979 to 1990. In the 1980s, the U.S. government, in apparent fear of the Sandinista's "pro-Cuban" orientation, infamously directed funds towards revolutionary troops—the "Contras"—in the hopes of installing a government in Nicaragua more acceptable to the U.S. administration of the time. The U.S. was subsequently accused of violating Nicaraguan sovereignty and ordered by the International Court of Justice to pay $12 billion to Nicaragua in compensation (Morrison, 1987). The 1980s were characterized by violent fighting between the Contras and the Sandinistas, until a truce was signed in 1989.

[10] This analysis focuses on Nicaragua because the data available is much more extensive than that for Honduras, though the eye of the storm never crossed the border into Nicaragua.

[11] Other hurricanes that have affected Nicaragua since 1985 (when fatality records begin) include Joan (1988, with an estimated 150 fatalities) Gert (1993, 11 fatalities), Cesar (1996, 42 fatalities), Beta (2005, 6 fatalities), Felix (2007, 130 fatalities), and Ida (2009, 0 fatalities).

Mitch in Nicaragua, but other economic and social consequences of Mitch have received attention in the academic literature. Premand (2008) finds a limited and short-term negative economic impact from damage due to Mitch, but no discernible effect on economic growth. Van den Berg (2010) presents evidence that, despite its heavy damage to agriculture, the hurricane did not induce substantial numbers of people to change their strategies for generating income. Jakobsen (2012) finds that Mitch had a significant negative effect on the ownership of durable goods and assets, that the poorest households were affected disproportionately, and that there is "strong suggestive evidence of a geographical poverty trap within the shock-affected areas of the country."

However, of these analyses, all but Premand (2008) measure hurricane exposure using a governmental designation of which areas were affected. This designation is derived from the decision by the Instituto Nacional de Estadística y Censos (INEC) to survey households in the areas INEC determined were affected by the hurricane, but the process by which this designation was determined is not transparent.[12] Given the claims by the opposition party and many in the media (described in Olson et al., 2001) that the government's response was influenced by political affiliations, it is questionable whether this designation accurately reflects the hurricane damage. Following Premand (2008), we use independent precipitation data to construct a measure of hurricane impact that is free of political influences.

III Empirical Strategy

The basic idea, to identify the effects of a catastrophic storm on the micro-level distribution of aid resources, is to (a) estimate the relationship between the impact of the storm and the subsequent distribution of aid and (b) establish convincing evidence that such estimates are unlikely to be driven by factors coincidentally related to the impact of the storm,

[12] The criteria for this determination are not described anywhere in detail (see Premand, 2008). The only description of the process of which we are aware comes from the World Bank (2001): "Households were selected for inclusion in the post-Mitch survey strictly on the basis that they were located in areas that were: (a) affected by the hurricane; and (b) included in the original 1998 LSMS.

including prior storms or historical patterns in storm risk. The extent of the data on aid allocations available for Nicaragua, which spans from four years before to seven years after Hurricane Mitch, allows for this.

We model household h's receipt of aid separately from each source—either government or NGO—and separately for each period: four-to-zero years before the hurricane, the short term (zero-to-three years after the hurricane), and long term (three-to-seven years after). The basic models for the receipt of aid, contributed to by households h in municipalities m, are captured in Equation 1, where we also control for household characteristics X_h that may influence the probability that a household receives aid. We present estimates from linear probability models, though the estimates from binary logit models are qualitatively very similar to the presented results (and available upon request).

$$AID_{hm} = \alpha + \delta_1 Hurricane_m + \delta_2 Sandinista_m + \delta_3 (Hurricane_m \times Sandinista_m) + \beta X_h + \epsilon_{hm} \tag{1}$$

The main explanatory variables of interest are the municipality-level (m) precipitation-based measure of hurricane impact ($Hurricane_m$) and the political affiliation of the leadership in municipality m (captured by the indicator, $Sandinista_m$). Any differential effects will therefore be captured by the interaction of these two covariates ($Hurricane_m \times Sandinista_m$). These measures vary at the municipal level, so to allow for the possible correlation of unobserved factors between households in the same community, we allow for clustered standard errors at the municipality level.[13]

A Challenges to identification

There are two obvious challenges to identifying the causal effect of a hurricane on aid allocations. First, in order to infer from $\hat{\delta}_1$ the causal effect of Hurricane Mitch on aid receipt, $Hurricane$ is assumed to vary independently of unobserved factors that themselves

[13] There are 125 unique municipalities represented in the LSMS data set.

influence the distribution of aid. One way the estimates might be biased by a correlation of the hurricane's impact with an omitted variable is if the impact of hurricanes is correlated over time. Past hurricane impacts could affect subsequent aid allocations through their effects on prior aid allocations, or on other factors that affect aid, such as levels of economic development.

However, the evidence presented in Section C suggests that this is unlikely to be the case—the historical impact of hurricanes across Nicaragua is reasonably uniform. This increases our confidence that regression estimates of the impact of Hurricane Mitch on aid allocations are unlikely to suffer from bias due to omitted variables related to hurricane risk. In the results, we also control for the 1996 impact of Hurricane Cesar, the most recent hurricane prior to Mitch. Hurricane Cesar was significantly smaller than Mitch and not nearly as destructive, though the extent to which it may have affected aid flows is likewise an empirical question. Including Hurricane Cesar as a control leaves the estimates of interest largely unchanged while their precision increases.

Another concern regarding the potential for unobserved variables to influence the results is that the impact of Hurricane Mitch might be related coincidentally to some other, unobserved, factor that influences aid. To speak to this, and in the spirit of a falsification test, we use data on aid allocations during the period before Hurricane Mitch to verify that the estimates we present are not simply reflective of pre-hurricane patterns of aid distribution.

Second, in conditioning the variation in AID_h on controls we are separately capturing potential confounding influences so as to leave the effects of the key variables identified. In so doing, it becomes important that these controls not be outcomes of the hurricane themselves—that is, they must not be caused by $Hurricane_m$. As it is possible that household characteristics measured *after* the hurricane could both (a) be affected by the hurricane and (b) affect the probability that a household receives aid, we use pre-hurricane measures of controls, collected in the 1998 wave of the LSMS.[14]

[14] In the language of Angrist and Pischke (2008), the post-hurricane measures of these variables are "bad controls" because they were not pre-determined at the time of the hurricane. For example, the hurricane's destruction of agricultural lands

Focusing on the sample of households that is surveyed both before and after the hurricane introduces the possibility that systematic patterns in attrition from the survey could affect the results. The rate of attrition between LSMS Waves I and II is 26 percent, which is not unusually high.[15] Nonetheless, we conduct a formal test of whether there are systematic differences in household attrition across levels of hurricane impact, estimating a linear-probability model,

$$Attrit_{hm} \quad = \quad \alpha + \delta Hurricane_m + \beta X_{1998,h} + \gamma(Hurricane_m \times X_{1998,h}) + \epsilon_{hm} \qquad (2)$$

where $Attrit_h$ equals one if 1998 household h was not resurveyed in 2001, and is equal to zero otherwise. Estimated standard errors again allow for clustering at the municipal level.

Table 2 presents estimates of the parameters in Equation 2. In the simplest specification, the probability of attrition is increasing in hurricane exposure (Column 1), though this relationship is not robust to the inclusion of household control variables, as shown in Column 2. There are some systematic relationships between attrition and household characteristics (Column 2), however there is no systematic difference in attrition across levels of hurricane exposure and any of the key variables of interest (aid from the government, aid from NGOs, or Sandinista representation), or any of the other independent variables for that matter, as indicated by the absence of any statistically significant coefficients on the interaction terms in Column 3. A test of the joint significance of the variable indicating receipt of aid from the government and its interaction with $Hurricane$ fails to reject the null hypothesis of no relationship ($p = 0.67$), as does a similar test for NGO aid ($p = 0.32$). An F-test of the joint significance of all of the interaction terms also fails to reject the null hypothesis that all terms are zero ($p = 0.25$). Thus, there is no evidence of systematic attrition that would bias

could cause an individual to pursue more education, which might in turn increase the probability that he receives aid. If there are positive effects from both Hurricane and education on the probability of receiving aid, the inclusion of the post-hurricane measure of education in a regression will wrongly attribute part of the effect of the hurricane to education.

[15] This is close to the attrition rates in the Panel Study of Income Dynamics in the U.S. (see Fitzgerald, Gottschalk and Moffitt, 1998), and comparable to attrition in other panel surveys in developing countries (see Deaton, 1997). Of the 4,020 households surveyed in 1998 with complete data, 74 percent were surveyed again in 2001. Of these, 89 percent were re-surveyed in 2005.

estimates of the impact of the hurricane or Sandinista representation (or their interaction) on aid allocations from either source.

IV Data

The data for this analysis come from three sources. We use weather data from the British Atmospheric Data Center to construct an exogenous measure of the spatial variation in the extent of hurricane's impact, and survey data from the World Bank's Living Standards Measurement Study to measure allocations of aid in Nicaragua. These two data sets are discussed in detail in Sections A and B.

To capture the political relationships between the national government and local populations, we use the political party affiliation at the time of Hurricane Mitch of the elected *alcaldes*, the municipal-level leadership position in Nicaragua. These data come from Nicaragua's Consejo Supremo Electoral.[16] In 1998, 51 *alcaldes* were Sandinistas and the remaining 92 were members of the ruling coalition led by the PLC.

A Data on aid allocations and household characteristics

For information on the allocation of aid in Nicaragua, we use the World Bank's Living Standards Measurement Study (LSMS) conducted by Nicaragua's Instituto Nacional de Estadística y Censos (INEC). The LSMS is a nationally representative household survey developed by the World Bank that has been conducted in dozens of countries since the mid-1980s.[17] The survey collects extensive information on household economic activity, education, and demographics. Respondents are identified geographically by their municipality (the secondary administrative unit in Nicaragua, similar to counties in the US) and we use this information to match the household survey data with the precipitation and political

[16] Nicaraguan election results can be accessed via http://www.dgapp-cse.gob.ni/

[17] For a detailed description of the LSMS surveys, see Grosh and Glewwe (1995) or the World Bank's LSMS website at http://iresearch.worldbank.org/lsms/lsmssurveyFinder.htm.

data.

In Nicaragua, the LSMS survey was administered three times (Wave I in 1998, Wave II in 2001, and Wave III in 2005). An important feature of these data sets is the timing, relative to Hurricane Mitch, of the periods reflected in the information on aid allocations.[18] Figure 2 presents a timeline of the relevant events. The information collected in LSMS Wave I, conducted several months before Hurricane Mitch, reflects aid allocated during 1994 to 1998 (pre-Mitch). The information collected in LSMS Waves II and III reflects aid allocations during 1999 to 2001 and 2001 to 2005, respectively. We refer to these periods as "before", "short term", and "long term".

The information on aid allocations in the LSMS reflects the household head's answer to the question: "During the period from .... to .... , has any member of this household benefitted from ...[X]... ?" The types of activities [X] for which the question is asked include the construction or improvement of roads, health clinics, and schools; the installation or repair of latrines, sewers, and electricity; the provision of health information, nutritional education, job training, and legal assistance; and direct donations of food or medicine. A subsequent question asks about the entity responsible and allows me to determine whether the aid was provided by the government or NGO.

The answer to this question provides a binary indicator of whether any member of the household benefitted from the particular aid activity in question. We combine the answers across the different aid activities to create a variable for each household indicating whether any member benefitted from aid provided by NGOs, and a separate variable indicating aid provided by the government.[19] These are the two main outcomes of interest analyzed in this paper. They do not measure the intensive margin of aid, but the approach is similar to that used in other studies, such as Francken, Minten and Swinnen (2012) and Morris and Wodon

[18] There was also a partial wave of the Nicaragua LSMS conducted in 1999, in the wake of the hurricane, but it was incomplete. Attempts to survey households in the hurricane-affected areas (as determined by INEC) were much less successful in the 1999 wave than in the 2001 wave, and no attempts were made to survey households in areas that were not affected by the hurricane. Thus, the 2001 wave provides the closest-in-time post-hurricane measure of aid across all levels of hurricane exposure.

[19] It could be informative to analyze the aid activities separately. However, the various sub-categories change across the survey years and consistency across surveys requires the combination of many categories.

(2003), who point out that it is difficult to build a reliable measure of the intensity of aid allocations even when more detailed information is available.[20]

The selection of the sample is discussed in greater detail in Section III, but we note here that we focus on households that were surveyed both before and after Hurricane Mitch (i.e., in LSMS Waves I and II). There is the possibility that systematic patterns in attrition could influence the results, however, we analyze patterns in attrition and test for this possibility (in Section A) and find no such evidence.

Descriptive Statistics are presented in Table 1. The household characteristics used in the analysis as control variables in the regressions include the education and gender of the household head, household size, per capita household consumption, and indicators of urban locality, access to electricity, and ownership of a television.

Table 1 also includes the precipitation-based measure of hurricane impact for Hurricane Mitch ($Hurricane$). The construction of this measure is described in detail next (in Section B). Simply put, $Hurricane_m$ is the ratio of rainfall during the hurricane period to average rainfall, measured at the municipality level (m). For example, $Hurricane_m = 1.75$ means that municipality m experienced 75 percent more rainfall during the hurricane period than its historical average.

B Measuring hurricane impact with precipitation data

To measure the impact of the hurricane, we use precipitation data from version 3.21 of the Climatic Research Unit time-series data set constructed by the British Atmospheric Data Center at the University of East Anglia, UK.[21] While other forces during a hurricane, such as strong winds, can also cause damage, reports of damage from Hurricane Mitch and other hurricanes that have affected Nicaragua point most frequently to precipitation and the

[20] Aid is often not given as cash but as food and clothes or other goods and assistance, or via the construction of public goods, but it is not straightforward to measure the degree to which a public good, such as a re-constructed bridge, benefits one household differently than another, and households differ in their absorptive capacity to make use of clothes, medicine, and other private goods.

[21] The data are publicly available at http://badc.nerc.ac.uk/home/index.html

subsequent flooding and landslides as the main cause (Hellin, Haigh and Marks, 1999).

The CRU precipitation data are constructed using information from over 4,000 weather stations worldwide. They are reported at a monthly frequency on a 0.5 degree latitude by 0.5 degree longitude grid, which is about 50km-square at Nicaragua's latitude. From each grid-month, we construct a measure of precipitation for every municipality in Nicaragua by interpolating a value for each 0.02 degree cell, using the four nearest grid observations weighted inversely by distance.[22] We then take the average across all 0.02 degree cells contained within each municipality's borders. This is a similar approach to that taken by others when associating weather data with survey data that reports the geographic location of respondents by administrative area (e.g., Strobl, 2012).

Figure 1 depicts the three steps in this process: Panel A presents Nicaragua's municipal boundaries overlaid with the original 0.5 degree precipitation data grid; Panel B shows a color-scaled example of the subsequent distance-weighted estimates for each 0.02 degree cell; and Panel C shows a color-scaled map of the municipal averages for an arbitrarily chosen sample month (here, July 1998).

It is important to recognize that areas differ in their capacity to absorb precipitation and their propensity for flooding or landslides, conditional on a given level of precipitation. For example, in one month, a heavy rainfall of, say, four inches is more likely to cause flooding and damage in an area that normally gets one inch of rain than in an area that regularly gets five inches of rain. To incorporate this heterogeneity in resilience into the measure of a given hurricane's impact, we calculate the historical average precipitation for each municipality during each calendar month, excluding hurricane months, for the twenty-five years prior to each hurricane. We exclude hurricane months from this calculation so that this average reflects typical, non-hurricane precipitation levels.

We then take the impact of hurricane h in municipality m to be the ratio of precipitation during the month of the hurricane to the average precipitation (over the previous twenty-five

[22] Calculations were completed using ESRI's ArcGIS software, v10.1.

years) that the municipality experienced during the same calendar month n during which hurricane h occurred.[23]

$$Hurricane_{mh} \quad = \quad Precip_{mh} \;/\; \overline{Precip}_{mn}$$

where

$Precip_{mh}$	$=$	precipitation in municipality m during the month of hurricane h
$\overline{Precip}_{mn}$	$=$	Average precipitation in municipality m in the calendar month n during which hurricane h occurred, excluding hurricane months, over the prior 25 years

For Hurricane Mitch, $Hurricane_m$ ranges from a low of 1.59 to a high of 2.05. The average is 1.75, which means that each municipality experienced, on average, 75 percent more precipitation during the month of Hurricane Mitch (October, 1998) than it typically experienced in the month of October over the previous 25 years.

C Geographic patterns in the impact of hurricanes: 1960-2010

This section presents a summary of the geographic variation in hurricanes across Nicaragua since 1960 (when hurricane tracking data for this region first became available). An important feature of the evidence is that the impact of hurricanes across Nicaragua is reasonably uniform and, therefore, estimates of the influence of Hurricane Mitch on the allocation of aid are unlikely to be biased by unobservable factors that might be correlated with hurricane risk, or driven by hurricane risk in general rather than the specific impact of Hurricane Mitch. In the results, we also control for the impact of Hurricane Cesar, the most recent hurricane prior to Mitch.

The measure of hurricane impact (*Hurricane*) described in Section B reflects the variation in hurricane intensity geographically within Nicaragua during a single hurricane, and

[23] There are no hurricanes in the sample whose impact spanned across multiple months.

across different hurricanes. We construct this measure for every municipality for each of the fourteen months during which a hurricane passed within 200 miles of Nicaragua between 1960 and 2010.[24] Figure 3 shows the distribution of this measure across all of these hurricanes.

The average hurricane impact, across all hurricanes and all municipalities, is 1.26. This means that during a month in which a hurricane passes within 200 miles of Nicaragua, the average municipal rainfall is 26 percent higher than its non-hurricane seasonal average. (For Mitch, $Hurricane_m$ ranges from 1.59 to 2.05.) Figure 4 shows the timeline of hurricanes affecting Nicaragua. Each vertical scatter-plot depicts the distribution (across municipalities) of the values of $Hurricane_m$ during each hurricane.

To see the impact of hurricanes leading up to Mitch, which might have lagged effects on aid flows, Figure 5 contains maps that depict $Hurricane_m$ for Mitch and the three previous hurricanes. Each of these maps is on its own scale, which highlights the geographic (cross-sectional) variation in the impact of each hurricane. The impact from Hurricane Mitch was largest in the north-central region of Nicaragua. During the three hurricanes before Mitch, the largest impacts were experienced in the south-west during Cesar (1996), the north-west during Gert (1993), and the north-east during Joan (1988).

To get a sense of overall hurricane risk, rather than recent impacts, Figure 6 shows the point estimate, for each municipality, of the mean impact across all hurricanes that affected Nicaragua from 1960-2010, along with 95 percent confidence intervals. The majority of the estimates fall within a tight band around the national average, and no municipality has a mean impact that differs from the national average at a significance level of five percent. The variation of the mean impact across municipalities can be seen geographically in the top map in Figure 7. This figure also includes maps of the impacts during Mitch and the three prior hurricanes, all on the same scale, to provide context to the map of the average municipal impacts (this also reveals the time-series variation across these hurricanes).

[24] Hurricane strength tropical cyclones are typically about 300 miles in diameter, though with considerable variation. The 200-mile cutoff represents a natural break point in proximity to Nicaragua among all hurricanes that occurred in the greater Central American region during the period studied. This set of hurricanes was determined using the Weather Underground's Hurricane Archive, which can be accessed at http://www.wunderground.com/hurricane/hurrarchive.asp

In addition to considering the intensive margin of hurricane impact, it is useful to consider the extensive margin. Table 4 shows the municipal incidence of hurricanes using a higher ($Hurricane > 1.75$) and a lower ($Hurricane > 1.50$) threshold to indicate whether a municipality was affected. Between 1960 and 2010, nearly all municipalities—138 out of 143—experienced between 2 and 4 hurricanes as measured by the lower threshold. Using the higher threshold, most municipalities (98 out of 143) experienced one hurricane, and no municipality experienced more than two.

Taken altogether, the evidence presented shows that the impact of hurricanes, along both the intensive and extensive margins, is remarkably similar across Nicaraguan municipalities.

V Results

The estimates of the effect of the hurricane on the probability that a household receives aid are presented separately for each time period (before, short term, and long term) and each source of aid (government or NGOs). The estimates are presented in chronological order to reveal the evolution over time of the response to the hurricane by each source of aid.

The estimates of the relationship between pre-hurricane aid allocations and the future impact of the hurricane are presented in Table 5. They serve as a simple verification of the identification strategy. Given that aid allocations before Hurricane Mitch should be unrelated to the future impact of the hurricane, testing whether there are any such relationships serves as a falsification test. As seen in Table 5, there is no evidence of a statistically significant relationship between pre-hurricane aid and hurricane impact. This supports a causal interpretation of the estimated effects of the hurricane impact on post-hurricane aid allocations, as discussed in Section III. Additionally, there are no pre-hurricane relationships between political affiliations and the allocation of aid by the government or by NGOs.

The main results showing the determinants of aid allocations made by the Nicaraguan government and NGOs in the first three years following Hurricane Mitch are shown in Table 6. The estimated coefficient on *Hurricane* in Column 1 is not statistically different from zero, suggesting that the government *did not* allocate more aid to households that experienced greater hurricane damage as measured by precipitation.

The models presented in Columns 2 and 3 of Table 6 include the variable *Sandinista*, which indicates whether the political leadership of a household's municipality is affiliated with the main opposition, and *Sandinista* interacted with *Hurricane*. There is no affect of this political representation on average (Column 2), but the estimates in Column 3 reveal a significant relationship between the interaction of the hurricane impact and municipal political affiliations. The relationship is striking: consistent with their complaints at the time, many Sandinista areas were much less likely to receive government aid. This effect is concentrated among the municipalities that experienced a smaller impact during the hurricane. Among households in the least-affected municipalities (*Hurricane*=1.59), those represented by the Sandinistas were about 26 percent (all percents relative to the mean) less likely to receive governmental aid than those represented by the ruling coalition (using point estimates from Column 3, the difference in these areas in the propensity to receive aid associated with Sandinista representation is (–1.10+0.59*1.59)/0.62=–0.26).

Estimates of the determinants of NGO-provided aid are presented in Columns 4-6 of Table 6. These estimates show that during the three years following the storm the NGO response to Hurricane Mitch was different from the government's response in two fundamental ways. First, aid allocations by NGOs were *not related* to political affiliations. Second, unlike government aid, NGOs actually did respond to the physical impact of the hurricane. The probability that a household received aid from an NGO was significantly higher in municipalities that were hit harder by the hurricane. Using the point estimate (0.37) of the impact of Hurricane on NGO aid from Column 4, the results suggest that households in the hardest hit areas were 74 percent more likely to receive NGO aid than those that experienced the average impact.[25] This effect is large on its own, and appears even larger in the context of the non-response by the government.

The last wave of the LSMS, conducted in 2005, sheds light on the longer term evolution of the effect of the hurricane on aid allocations. Table 7 presents the estimates of the models of longer-term aid allocations, from both NGOs and the government, three to seven years after the hurricane, as reported by the 2,645 remaining households from the main sample.[26] The estimates suggest that by this time, the Nicaraguan government was allocating more aid to areas that experienced more damage during Hurricane Mitch, with households in the most affected areas about 17 percent more likely to receive aid than households that experienced the average impact.[27] Furthermore, the influence of political affiliations on government aid allocations seen in the earlier period is now gone. The long-term behavior of NGOs is similar to their shorter-term behavior, in that they continue to allocate significantly more aid to areas that were hit harder by the hurricane.

It is perhaps not surprising that Hurricane Mitch has had such a long-term effect on aid allocations in Nicaragua, given the extensive damage it caused. During the early 2000s, among all countries in the western hemisphere, only Haiti had lower per-capita GDP than Nicaragua. Repairing the 1500 miles of roads and 300 schools that were destroyed requires substantial effort, especially in the poor, rural parts of Nicaragua that were hit hardest by the hurricane.

The results also suggest interesting patterns in the allocation of aid along wealth lines, and across urban and rural areas. Households in urban areas are less likely to receive aid from NGOs throughout the study period, with the largest difference in the period immediately following the hurricane. Initially, the government is also less likely to provide aid to urban households, though by the long term period they have switched and are more likely to provide aid to urban areas. Both sources are less likely to provide aid to wealthy households

[25] The calculation is [(2.05-1.75)*0.37]/0.15=0.74

[26] An analysis of attrition, including evidence that it appears unlikely to bias these estimates, can be found in Section A

[27] Using the point estimate from Column 1, the calculation is [(2.05-1.75)*0.45]/0.78=0.17

before the hurricane, but there is no relationship between wealth and likelihood of receiving aid immediately following the hurricane. the lack of such a relationship between household consumption levels and aid in the period just after the hurricane is perhaps surprising, as it is often expected that aid, especially from NGOs, is directed towards poorer households. However, Nicaragua is a largely rural country and poverty is much higher in the rural areas, so the strong negative relationship between NGO aid and urban areas may perhaps reflect patterns along wealth levels, if NGOs target their efforts geographically rather than to specific households within a given area.

VI Conclusion

This paper investigates the political economy of development aid allocations at the micro-level, using Nicaragua as an example. The fortuitous timing of the collection of extensive data on aid received by Nicaraguan households, relative to the catastrophic impact of Hurricane Mitch, allows for an examination of how non-governmental organizations (NGOs) differ from the domestic government in their response to an arguably objective measure of need (i.e., the impact of a hurricane). The extent of the available data also allows for important methodological improvements on existing studies of disaster aid and the first estimates, to the best of my knowledge, of the long term impacts of a natural disaster on development resource allocations. Furthermore, despite predictions that the intensity of tropical cyclones will increase substantially over the next century (Knutson et al., 2010; Pachauri and Reisinger, 2007; Scheraga et al., 2003; Solomon et al., 2007), there is limited empirical evidence on the micro-level aid response to these storms specifically, and to natural disasters in general. This study contributes to filling that gap. The setting studied is also relevant because Nicaragua has similarly low levels of development to many other areas prone to extreme storms, and Hurricane Mitch, while perhaps an outlier in terms of storm severity at the time it occurred, is arguably representative of the extremely powerful hurricanes that are predicted to occur with greater frequency (see Knutson et al., 2010).

To estimate the effects of a natural disaster on aid allocations requires appropriately timed data collection, and we are fortunate to have such an opportunity in Hurricane Mitch's arrival in Nicaragua. We use survey data containing information on aid received by Nicaraguan households that corresponds to three separate blocks of time: zero to four years before the hurricane, zero to three years after (the "short term"), and again three to seven years after (the "long term"). The measures of aid included in the survey are broad and do not permit a detailed analysis by aid type. However, they reflect a household's access to basic resources that are important to economic development, including the construction or repair of roads and schools, improvements in access to electricity and drinking water, and direct provisions of food and medicine. With these data, we estimate the effect of the storm on short- and long-term aid allocations and then test for differences across political affiliations, measured through municipal election outcomes.

In addition to the use of extensive data on aid allocations, this research improves on existing studies that estimate the effects of natural disasters on aid allocations in two other important ways. First, in order to alleviate concerns that the choice of disaster impact designations might be influenced by factors unrelated to damage, such as political connections, we use precipitation data recorded at a relatively fine geographic scale to construct an exogenous measure of the hurricane's impact. While it is possible that official reports of disaster damage could reflect strategic efforts to influence the allocation of aid, these precipitation data should be free from any such manipulation.

Second, we carefully consider the potential for the estimates to be biased by unobserved factors that might influence the distribution of aid. It is possible that patterns in hurricane risk, as opposed to the incidence of any particular storm, could determine aid allocations either directly or indirectly through a correlation with unobserved characteristics (such as prior aid allocations) that might also systematically affect the distribution of aid. A detailed examination of geographic variations in the historical impact of hurricanes across Nicaraguan municipalities reveals that no parts of Nicaragua are particularly more or less likely to be struck by hurricanes and, therefore, suggests that the impact of hurricanes in Nicaragua is independent of geographic or population characteristics that might influence the distribution of aid. The data on pre-storm aid allocations also allow the consideration of the possibility that the impact of the hurricane was coincidentally related to existing patterns in aid distribution. We find no evidence of a such a relationship, which, along with the use of exogenous rainfall data, supports a causal interpretation of the estimates.

The analysis of aid allocations made by the domestic government separately from those made by NGOs proves to be informative. Following the catastrophe, short-term allocations of aid by NGOs were made according to the precipitation-based measure of the hurricane's impact, with the most severely affected households about 74 percent more likely to receive aid from NGOs than those that experienced the average impact. Furthermore, we find no evidence that NGO aid was influenced by political affiliations. These results stand in stark contrast to the allocation of aid by the government, which also responded to the hurricane in the short term, but not as one would hope. Among areas that experienced less than the average hurricane impact, the government was significantly *less likely*, by about 20 percent, to provide aid to households in areas led by the major opposition party (relative to similarly affected households in areas controlled by the ruling coalition). While aid was diverted away from these opposition-controlled areas, the government *did not allocate more aid* to the areas that were more heavily affected by the hurricane.

We also find that Hurricane Mitch had a long-lasting impact—extending at least three years after the storm—on the allocation of aid in Nicaragua. As in the short term, NGOs were more likely to allocate aid in the long term to households that experienced a more severe impact during the hurricane. Unlike in the short term, the Nicaraguan government actually did allocate more aid in the long term to households that experienced a larger hurricane impact. During this time, households that experienced the strongest effect were about 17 percent more likely to receive aid from the government than those that experienced the average impact. That a hurricane can have such a long-term affect on the allocation of aid within a country is perhaps surprising. However, Mitch was the deadliest Atlantic hurricane in over 200 years and caused significant destruction across large parts of Nicaragua. Repairing such extensive damage to roads, bridges, agricultural lands, and other infrastructure would be challenging even in wealthy countries, and is likely to be more difficult in a developing country such as Nicaragua.

Given the large differences in the responsiveness of NGOs and the government to the catastrophe, and their differential sensitivities to the political affiliations of the municipalities affected, it is tempting to interpret these results as somewhat disheartening. On the one hand, the political maneuvering reflected in the post-hurricane governmental allocation of aid, and the lack of a response to the physical measure of hurricane damage, suggest that aid might be transmitted more effectively through non-governmental channels. On the other hand, the results may be specific to a context that is characterized by low levels of economic development and contentious politics. As such, any application to other contexts should proceed with caution. That said, post-disaster reports in the media, such as those in the Philippines following Typhoon Haiyan in 2013, often claim that disaster recovery efforts are manipulated for political gain, and the analysis presented here is consistent with these sentiments.

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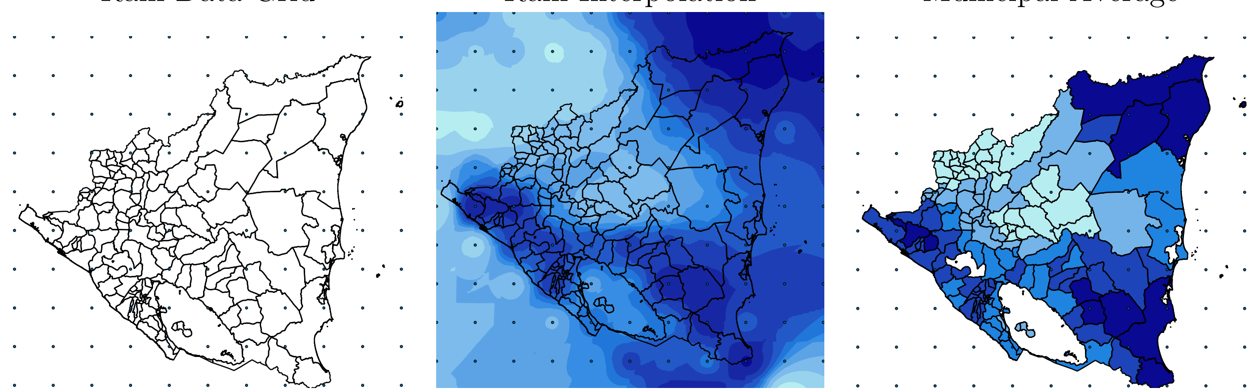
Figures

Figure 1: Precipitation Data Construction



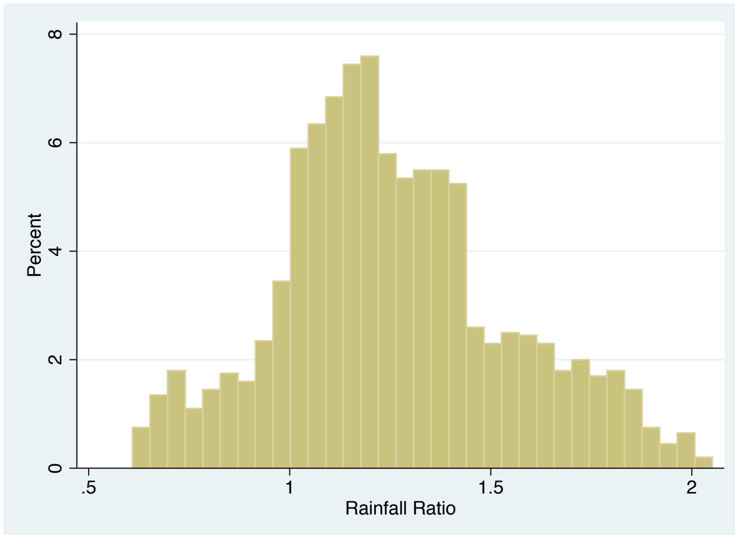
Notes: The left map depicts the 0.5 degree latitude by 0.5 degree longitude grid for which monthly precipitation data are available from the British Atmospheric Data Center's Climate Research Unit. These data are used to interpolate a measure of rainfall for each 0.02 degree cell from the four nearest observations, weighted inversely by distance (lower left). This measure is then averaged within each municipality to create a measure of rainfall at the municipal level (depicted lower right, for sample month (here, July 1998)).

Figure 2: Timeline of Hurricanes, Elections, and Data Collection

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Hurricanes			Cesar		Mitch							Beta
LSMS collected					I			II				III
Aid Period	[..................	"before"	....	]	[.......	"short-term"	.......]	[............	"long-term"	............]		
Households					4,020			2,960				2,645
Municipal Elections			x				x				x	
National Elections			x					x				

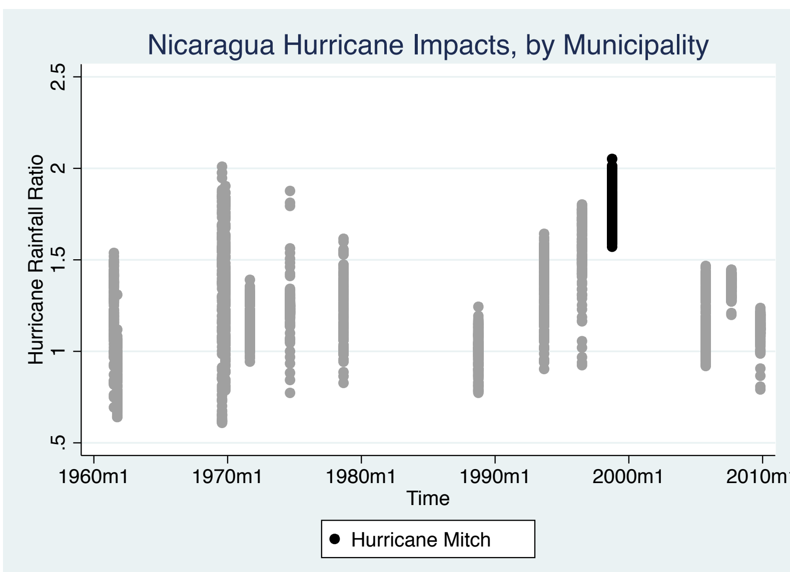
Notes: Hurricane Mitch occurred in October of 1998, after the collection of data in LSMS Wave I. Hurricane Beta occurred in October of 2005, after the collection of data in LSMS Wave III.

Figure 3: Distribution of the Hurricane Rainfall Ratio measure of impact for all hurricanes affecting Nicaragua from 1960-2010



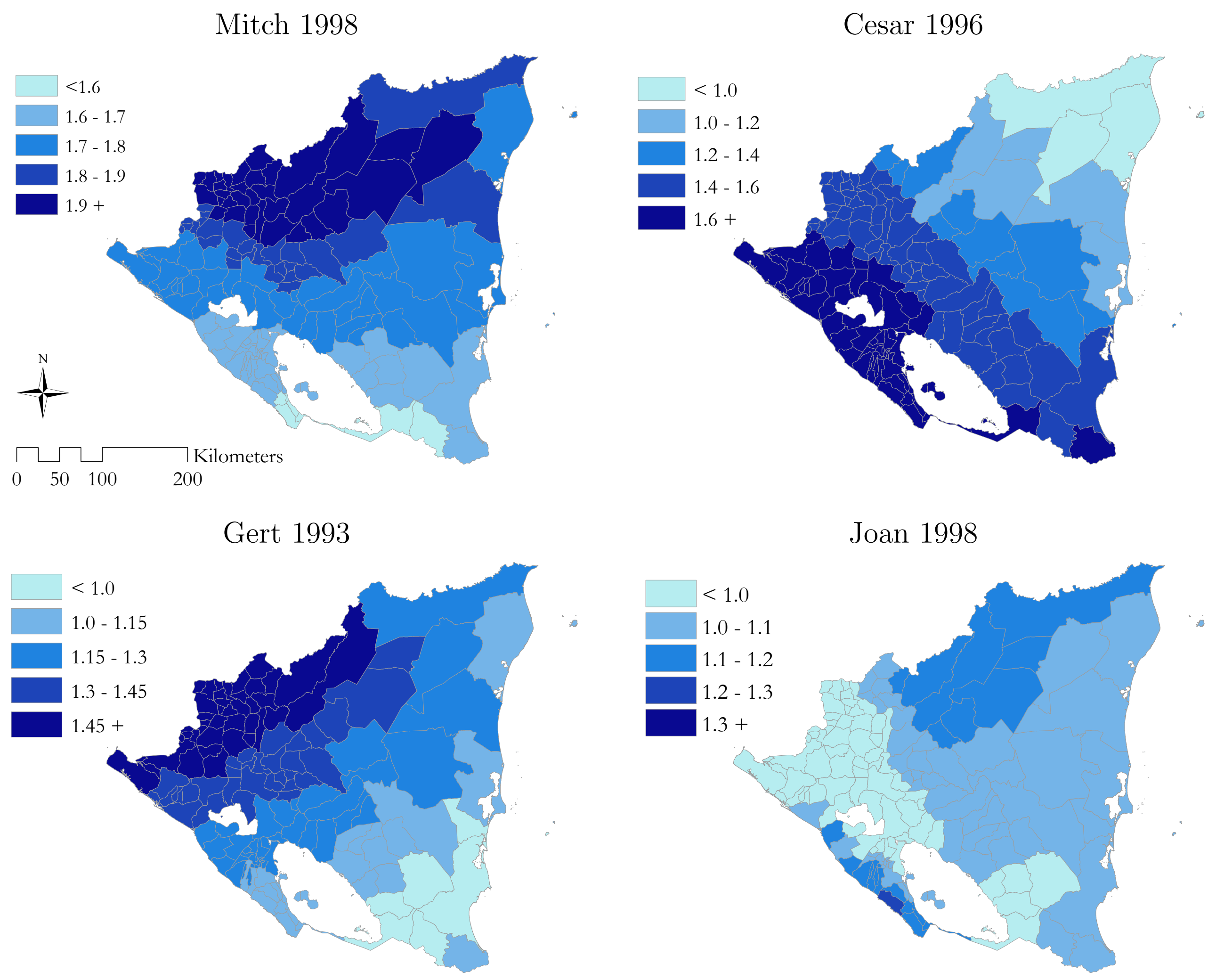
Notes: Construction of the Hurricane Rainfall Ratio is described in detail Section B. It is equal to the municipal rainfall during the hurricane month divided by the municipality's average, non-hurricane, rainfall for the same month over the prior 25 years. There are 2,002 total observations (143 municipalities times 14 hurricanes). The mass of this distribution that is less than one reflects the fact that some municipalities may experience below average rainfall at the same time that other municipalities are affected by a hurricane.

Figure 4: Timeline of hurricanes affecting Nicaragua: 1960-2010



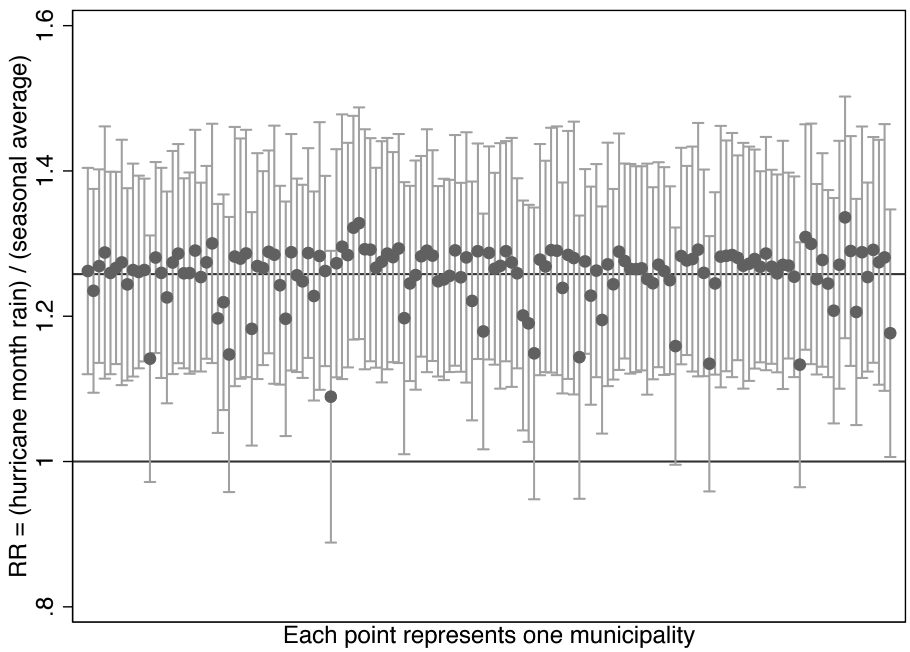
Notes: Each point represents one municipality during a hurricane. Construction of the Hurricane Rainfall Ratio is described in detail Section B. It is equal to the municipal rainfall during the hurricane month divided by the municipality's average, non-hurricane, rainfall for the same month over the prior 25 years.

Figure 5: Geographic Variation in Hurricane Impact (Rainfall Ratio)



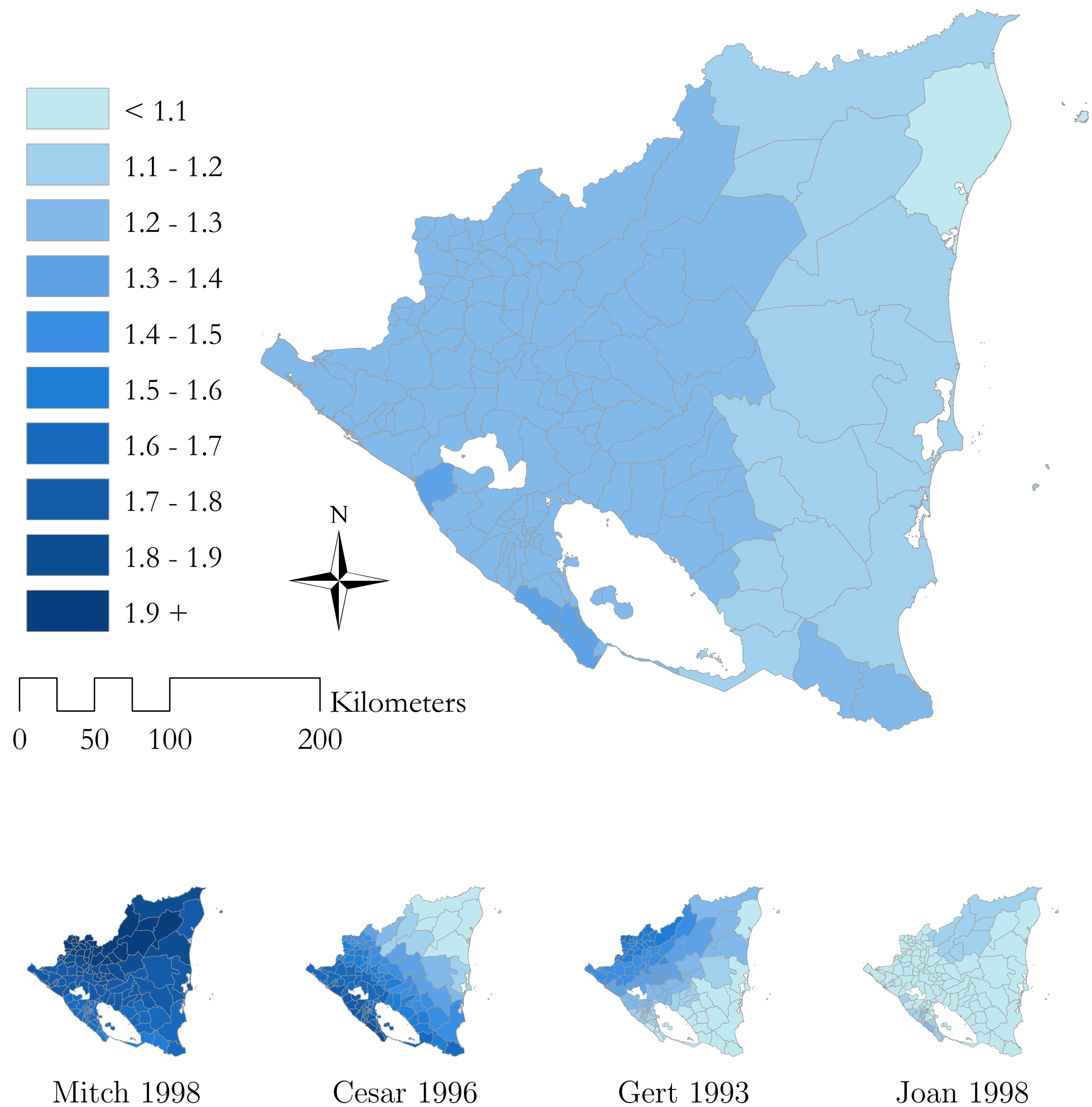
Notes: The maps are individually scaled to highlight the geographic variation in the impact of each hurricane. Construction of the Rainfall Ratio is described in detail Section B. It is equal to the municipal rainfall during the hurricane month divided by the municipality's average, non-hurricane, rainfall for the same month over the prior 25 years.

Figure 6: Average Hurricane Impact (Rainfall Ratio) by Municipality: 1960-2010



Notes: There are 14 hurricanes reflected in the data, and there are 143 municipalities in Nicaragua. Error bars represent 95 percent confidence intervals. Construction of the Rainfall Ratio is described in detail Section B. It is equal to the municipal rainfall during the hurricane month divided by the municipality's average, non-hurricane, rainfall for the same month over the prior 25 years.

Figure 7: Average Hurricane Impact (Rainfall Ratio): 1960-2010



Note: All maps use the same color scale. The small maps are provided to give context to the large map of the average impacts. Construction of the Rainfall Ratio is described in detail Section B. It is equal to the municipal rainfall during the hurricane month divided by the municipality's average, non-hurricane, rainfall for the same month over the prior 25 years.

Tables

Table 1: Descriptive Statistics – Households surveyed before and after Hurricane Mitch

		By Hurricane Impact	
	Full Sample	Above Median	Below Median
Hurricane Mitch Impact (RR)[a]	1.75	1.85	1.65
Pre-Hurricane Household Characteristics			
Household size	5.70	5.98	5.61
HH head has $\geq$ elementary education	0.32	0.23	0.40
HH head is female	0.28	0.25	0.31
Lives in urban locality	0.55	0.43	0.67
HH has electricity	0.64	0.48	0.79
HH owns a television	0.52	0.37	0.67
Consumption (annual, US$100 per person)	6.67	5.19	8.10
Locally represented by Sandinistas	0.31	0.38	0.24
Household Receipt of Aid			
Before Mitch: -4 - 0 yrs	0.68	0.65	0.70
from Nicaraguan government	0.59	0.57	0.61
from NGOs	0.15	0.16	0.15
Short Term after Mitch: 0 - 3 yrs	0.72	0.74	0.70
from Nicaraguan government	0.62	0.65	0.60
from NGOs	0.15	0.20	0.10
Long Term after Mitch: 3 - 7 yrs[b]	0.83	0.83	0.83
from Nicaraguan government	0.78	0.78	0.79
from NGOs	0.12	0.16	0.07
Households	2,960	1,456	1,504

[a] The construction of the rainfall-based measure of hurricane impact, the Rainfall Ratio (RR), is described in detail in Section B. It is equal to the municipal rainfall during the hurricane month divided by the municipality's average rainfall for the same calendar month over the previous 25 years, excluding months when a hurricane occurred.
[b] The samples are smaller in the long-term period (1,308 households with above-median impact and 1,337 with below-median impact (2,645 total households)). Selection of the sample and analysis of attrition are discussed in detail in Section III.

Table 2: Household Attrition and Hurricane Exposure for LSMS 1998 households

	Attrition between 1998-2001			Attrition between 2001-2005		
	(1)	(2)	(3)	(4)	(5)	(6)
Hurricane Mitch Impact (RR)	0.160**	0.047	0.061	-0.048	-0.064	-0.147
	(0.069)	(0.069)	(0.353)	(0.050)	(0.051)	(0.230)
Household size		-0.020***	-0.026		-0.010***	-0.020
		(0.003)	(0.041)		(0.002)	(0.028)
HH head has ≥ elementary education		0.057***	0.047		0.009	-0.094
		(0.017)	(0.292)		(0.015)	(0.217)
HH head is female		-0.070***	0.217		-0.020*	0.058
		(0.015)	(0.236)		(0.012)	(0.180)
Lives in urban locality		0.035*	-0.410		0.039**	-0.318
		(0.020)	(0.266)		(0.020)	(0.223)
Has electricity		-0.010	0.069		-0.017	-0.002
		(0.021)	(0.346)		(0.023)	(0.276)
Owns Television		-0.111***	-0.225		-0.040**	-0.019
		(0.022)	(0.339)		(0.017)	(0.250)
Received aid from government		-0.061***	0.192		-0.026**	-0.299*
		(0.017)	(0.259)		(0.011)	(0.179)
Received aid from NGO		-0.075***	0.374		-0.028*	0.075
		(0.018)	(0.282)		(0.015)	(0.162)
Opposition		-0.052**	-0.158		-0.034*	0.004
		(0.022)	(0.311)		(0.017)	(0.220)
log(Consumption per capita)		-0.023*	0.014		0.006	0.157
		(0.013)	(0.203)		(0.012)	(0.156)
Hurricane Mitch Impact						
× Household size			0.003			0.006
			(0.024)			(0.016)
× HH head has ≥ elementary education			0.006			0.060
			(0.169)			(0.127)
× HH head is female			-0.164			-0.045
			(0.136)			(0.102)
× Lives in urban locality			0.254			0.204
			(0.154)			(0.125)
× Has electricity			-0.046			-0.009
			(0.195)			(0.155)
× Owns Television			0.065			-0.013
			(0.196)			(0.145)
× Received aid from government			-0.144			0.156
			(0.148)			(0.102)
× Received aid from NGO			-0.253			-0.058
			(0.163)			(0.091)
× Opposition			0.060			-0.022
			(0.176)			(0.122)
× log(Consumption per capita)			-0.021			-0.086
			(0.115)			(0.089)
Households	4020	4020	4020	2960	2960	2960
R-squared	0.00	0.05	0.06	0.00	0.02	0.03
Mean of Dep Var	0.26	0.26	0.26	0.08	0.08	0.08
F test: Interaction terms jointly 0; Prob> F			0.25			0.21

Notes: Coefficients represent estimates from linear probability models. Significantly different than zero at 99 (***), 95 (**), 90 (*) percent confidence. Estimated standard errors are in parentheses, adjusted for any clustering at the municipal level. Mitch Rainfall Ratio ranges from 1.59 to 2.05 and represents the rainfall experienced during the hurricane as a percentage of the average non-storm rainfall, adjusted for seasonality.

Table 3: Attrition Model Parameter Estimates: Tests of Joint Significance

	Attrition between	
	1998-2001 (Table 2 Model 3)	2001-2005 (Table 2 Model 6)
Hypothesis	P-value	
$\beta_{ReceivedGovtAid} + \beta_{Mitch \times ReceivedGovtAid} = 0$	0.673	0.065
$\beta_{ReceivedNGOAid} + \beta_{Mitch \times ReceivedNGOAid} = 0$	0.315	0.813
$\beta_{Sandinista} + \beta_{Mitch \times Sandinista} = 0$	0.473	0.853

Notes: The table presents p-values from F-tests of the hypotheses indicated, derived using the parameter estimates from the models of attrition presented in Table ??.

Table 4: Municipal Hurricane Incidence 1960–2010 (as measured by Hurricane Rainfall Ratio (HRR))

Frequency of Hurricanes (X)	**Number of municipalities experiencing X hurricanes with impact:** HRR>1.75	HRR>1.50
0	26	0
1	98	3
2	19	50
3	0	76
4	0	12
5	0	2
6+	0	0
Total	143	143

Note: There were 14 hurricanes during the period considered. Construction of the Rainfall Ratio is described in detail Section B. It is equal to the municipal rainfall during the hurricane month divided by the municipality's average, non-hurricane, rainfall for the same month over the prior 25 years.

Table 5: Effect of Hurricane Mitch on Aid Allocations: 4 - 0 years before (Falsification Test)

Source of Aid:	Nicaraguan Government			Non-Governmental Organizations		
	(1)	(2)	(3)	(4)	(5)	(6)
Hurricane Mitch Impact (1998)	0.34	0.36	0.34	0.07	0.15	0.02
	(0.26)	(0.25)	(0.48)	(0.19)	(0.18)	(0.36)
Sandinista		-0.01	-0.05		-0.05	-0.34
		(0.05)	(0.83)		(0.04)	(0.60)
Sandinista × Mitch Impact			0.02			0.16
			(0.46)			(0.33)
log(Consumption per capita)	-0.06***	-0.06***	-0.06***	-0.04***	-0.04***	-0.04***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Lives in urban locality	-0.08**	-0.08**	-0.08**	-0.07**	-0.07**	-0.07**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Hurricane Cesar Impact (1996)	0.38**	0.39**	0.39**	-0.06	0.04	0.04
	(0.16)	(0.18)	(0.18)	(0.12)	(0.12)	(0.12)
Households	2960	2960	2960	2960	2960	2960
R-squared	0.04	0.04	0.04	0.03	0.03	0.03
Mean of Dep Var	0.59	0.59	0.59	0.15	0.15	0.15

Notes: Coefficients represent estimates from linear probability models. Estimated standard errors are in parentheses, adjusted for any clustering at the municipal level. Significantly different than zero at 99 (***), 95 (**), 90 (*) percent confidence. Hurricane Mitch Impact ranges from 1.59 to 2.05 and represents the rainfall experienced during the hurricane as a percentage of local average non-storm rainfall, adjusted for seasonality. Additional control variables included in the models but not presented are household size, gender and education of the household head, and indicators of household ownership of a television and access to electricity.

Table 6: Effects of Hurricane Mitch on Aid Allocations: 0 - 3 years after

Source of Aid:	Nicaraguan Government			Non-Governmental Organizations		
	(1)	(2)	(3)	(4)	(5)	(6)
Hurricane Mitch Impact (1998)	0.24	0.33*	-0.13	0.37***	0.40**	0.58**
	(0.18)	(0.20)	(0.26)	(0.14)	(0.16)	(0.27)
Sandinista		-0.06	-1.10**		-0.02	0.40
		(0.05)	(0.45)		(0.04)	(0.44)
Sandinista × Mitch Impact			0.59**			-0.24
			(0.26)			(0.26)
log(Consumption per capita)	-0.03	-0.03	-0.03	-0.01	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Lives in urban locality	-0.04	-0.03	-0.04	-0.10***	-0.09***	-0.09***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Hurricane Cesar Impact (1996)	0.05	0.17	0.16	0.21**	0.25*	0.25**
	(0.14)	(0.19)	(0.18)	(0.09)	(0.13)	(0.13)
Households	2960	2960	2960	2960	2960	2960
R-squared	0.01	0.01	0.02	0.06	0.06	0.06
Mean of Dep Var	0.62	0.62	0.62	0.15	0.15	0.15

Notes: Coefficients represent estimates from linear probability models. Estimated standard errors are in parentheses, adjusted for any clustering at the municipal level. Significantly different than zero at 99 (***), 95 (**), 90 (*) percent confidence. Hurricane Mitch Impact ranges from 1.59 to 2.05 and represents the rainfall experienced during the hurricane as a percentage of local average non-storm rainfall, adjusted for seasonality. Additional control variables included in the models but not presented are household size, gender and education of the household head, and indicators of household ownership of a television and access to electricity.

Table 7: The effects of Hurricane Mitch on Aid Allocations: 3 - 7 years after

Source of Aid:	Nicaraguan Government			Non-Governmental Organizations		
	(1)	(2)	(3)	(4)	(5)	(6)
Hurricane Mitch Impact (1998)	0.45***	0.53***	0.76***	0.51***	0.54***	0.46**
	(0.15)	(0.15)	(0.17)	(0.12)	(0.14)	(0.21)
Sandinista		-0.05	0.48		-0.02	-0.19
		(0.03)	(0.35)		(0.03)	(0.35)
Sandinista × Mitch Impact			-0.30			0.10
			(0.20)			(0.20)
log(Consumption per capita)	-0.04**	-0.04**	-0.04**	-0.01	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Lives in urban locality	0.11***	0.11***	0.11***	-0.06***	-0.06***	-0.06***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Hurricane Cesar Impact (1996)	0.20**	0.30**	0.30**	0.21***	0.25**	0.25**
	(0.09)	(0.13)	(0.12)	(0.07)	(0.10)	(0.10)
Households	2645	2645	2645	2645	2645	2645
R-squared	0.04	0.05	0.05	0.06	0.06	0.07
Mean of Dep Var	0.78	0.78	0.78	0.12	0.12	0.12

Notes: Coefficients represent estimates from linear probability models. Estimated standard errors are in parentheses, adjusted for any clustering at the municipal level. Significantly different than zero at 99 (***), 95 (**), 90 (*) percent confidence. Hurricane Mitch Impact ranges from 1.59 to 2.05 and represents the rainfall experienced during the hurricane as a percentage of local average non-storm rainfall, adjusted for seasonality. Additional control variables included in the models but not presented are household size, gender and education of the household head, and indicators of household ownership of a television and access to electricity.