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Direct and Indirect Effects of Extreme Weather Events and Potential Estimation Biases

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Abstract

The literature analyzing the effects of extreme weather events on social and economic outcomes has increased significantly in the last few years. Most of these analyses use either self-reported data about whether the storm affected the respondent or aggregated data such as precipitation at municipality level. We argue that these estimates might be biased due to the inclusion of households that are not directly affected but live close enough to be indirectly affected through economic or government assistance spillovers. Using data for Guatemala, we estimate separately the direct and indirect effects of Tropical Storm Stan on subjective economic well-being. We find that households that were directly affected by Stan are significantly more likely to report being poorer after the storm. We also find that the direct effects of the storm are similar in poor and less-poor agricultural municipalities. However, in non-agricultural municipalities, the effects are larger in less-poor municipalities. Reducing poverty rates might not be enough to address the problems related to climate shocks, which are expected to increase with climate change. We also find that households indirectly affected in non-poor municipalities reported being significantly worse off and households indirectly affected in poor municipalities reported being significantly better off. Given that shocks and responses to shocks will likely affect households that were not directly exposed, estimates of these effects are difficult to measure without simultaneously considering exposure data at both the household level and municipality level.

Key Words: climate, climate shock, Guatemala, well-being

JL Codes: Q54, I31, I32

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Direct and Indirect Effects of Extreme Weather Events and Potential Estimation Biases

Juan Robalino, Catalina Sandoval, and Alejandro Abarca*

1. Introduction

It has been well documented that climatic shocks significantly affect welfare (Skoufias 2003; Baez and Santos 2007; Carter et al. 2007; Rosemberg et al. 2010; Strobl 2011; Bustelo 2011). Some of the evidence suggests that the poorest households are affected the most (Rosemberg et al. 2010; Vicarelli 2010. It has been argued, for instance, that the poor participate relatively more in agricultural activities, which are highly susceptible to climate. Poor households might not only be more exposed but also less able to cope with climatic shocks. Lower income households have lower access to insurance and credit markets, which limits their capacity to cope with negative shocks (Morduch 1994; Mendelsohn 2012). Moreover, they might not be able to invest in physical and human capital that could mitigate the impacts of shocks. Along these lines, conditional cash transfers, which increase income, have been shown to be an effective tool to reduce vulnerability to negative shocks in general (Ospina 2011; Maluccio 2005), and to climate shocks in particular (Vicarelli 2010; De Janvry et al. 2006).

However, lower income households might also have mechanisms to reduce the impacts of shocks. For instance, lower income households that have consumption credit constraints might bypass profitable but risky opportunities in order to protect consumption (Morduch 1994). Empirical evidence supports the idea that poorer farmers in riskier environments tend to select portfolios of assets that are less profitable but less sensitive to rainfall variation (Rosenzweig and Binswanger 1993). In fact, in some contexts, poor families might be less affected by climate shocks than wealthier families. The poor may have many inexpensive alternatives that can help them adjust in case of a shock, while wealthier families may have specialized in activities more susceptible to climate (Mendelsohn 2012). The answer to the question of whether poorer or wealthier households are more vulnerable in the context of climate change is an empirical issue, as argued by Mendelsohn (2012).

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Using a subjective economic well-being measure, we test whether households in poor municipalities in Guatemala are less vulnerable to climatic shocks. We also test whether the answer to this question changes according to the municipality's dependence on agricultural activities. Specifically, we estimate the effects of Tropical Storm Stan, which strongly affected Guatemala in 2005, on whether a household reports being poorer in 2006 relative to 2000, controlling for household and municipality level characteristics.

Guatemala is an ideal country to test this hypothesis. Guatemala, like the rest of the Central American and Caribbean countries, is highly exposed to extreme climatic events that have resulted in deaths, damage to the environment and infrastructure, and impacts on the economy (Herrera 2003; ECLAC 2005; WB 2009; ECLAC 2010; UNICEF 2010; ECLAC 2012). Moreover, the country has been characterized by lagging social indicators, high levels of poverty, and income inequality (WB 2009). On top of this, it is expected that changes in climate variability will increase the occurrence and magnitude of extreme climatic events (ECLAC 2010; CCAD and SICA 2011; ECLAC 2012).

There are several challenges when identifying the effects of climatic shocks. First, many of the papers testing this hypothesis rely on self-reported shocks (Gitter 2005; Bustelo 2011; Ospina 2011). Other households that do not report being affected by a shock, even if living in the same municipality, are used as controls. These observations, however, could be affected by two forces. On one hand, impacts on infrastructure and the economy could have indirect negative effects on individuals within the community who were not directly affected – for example, by reducing economic activity. On the other hand, when a shock occurs, governments increase expenditures on relief efforts, through social programs and public investments in the areas affected (Cole et al. 2012; Besley and Burgess 2002). Households that live in affected areas and were not directly affected could become better off than they would have been if the shock had not occurred. Thus, using these indirectly affected households as controls can affect the estimates of the impact of the shocks in different directions.

Other papers have relied on climatic information in order to identify shocks (as in Vicarelli 2010 and Macours et al. 2012). However, precipitation data can be obtained only at aggregated levels such as municipalities. In that case, households that were not affected by the climatic shock, in municipalities that were affected, will be classified as affected. As argued before, the level of impacts varies between those directly affected and those indirectly affected. Some households are better off due to the shock and public investments that follow. Other households are worse off due to reduced economic activity. It is difficult to distinguish these effects when using only municipality level weather data. For instance, if remediation policies

target the poor, the differences between the impacts on the poor and non-poor will be biased because the indirect effects will confound the estimates and, as a result, the policy implications of the results will have to be revised.

We address this issue using a combination of self-reporting, government reports and climatic data. We classified affected households as directly affected by the storm and as not directly affected by the storm but located in a municipality affected by the storm. Using this information, we are able to estimate direct effects and indirect effects separately.

We find that the effect of the storm on the likelihood of reporting being poorer in 2006 with respect to 2000 is positive and significant. In agricultural municipalities, there is no significant difference between the effects on households living in poor and non-poor municipalities. However, the effects between poor and non-poor municipalities differ significantly in non-agricultural municipalities. Households in poorer municipalities are significantly less affected. This might be the result of government assistance that is targeting the poor. It could also be explained by the fact that households in poor municipalities have few assets and less to lose. These results were robust to different specifications and subsample analyses.

We also confirm our hypothesis that there are significant indirect effects of the storm and that they can be positive or negative. Indirect effects of Stan in non-poor municipalities increase the likelihood of reporting being poorer, especially in agricultural municipalities. In poor agricultural municipalities, the adverse indirect effect was also significant. However, indirect effects in poor and agricultural municipalities actually decrease the likelihood of reporting being poorer. This is again consistent with government support being targeted to the poor even if they were not directly affected by the storm.

These results are important for two reasons. Methodologically, they point out that, even if households declare that they were not affected by the shock, if they live close to where the shock occurs, their inclusion as control observations will bias estimates of the impact of shocks. This bias could be positive or negative because the indirect effects could also be positive or negative.

The results are also important because they show that policies to reduce vulnerability to climatic shocks should also be aimed at municipalities that are not poor. Increasing income and lowering poverty might not be enough to address the problems related to climate shocks, which are expected to increase with climate change.

The paper is organized as follows. In Section 2, we describe the data. In Section 3, we explain the empirical strategy. We present our results in Section 4. Finally, in Section 5, we conclude.

2. Data

We use data from the National Survey of Life Conditions (ENCOVI) implemented in 2006. The survey is implemented by the government statistical office of Guatemala (Instituto Nacional de Estadisticas). Households are drawn from the census database that is used as a sampling frame. There are a total of 13686 households in the sample. The sample is representative at the national level and for each of the 22 departments that form Guatemala.

We also use socioeconomic data from the 11th Population Census and 6th Housing Census, conducted in 2002. The data obtained from these sources are available at the municipality level.

2.1 Households' Subjective Economic Well Being

We use subjective changes in economic well-being as a dependent variable. Within the ENCOVI survey, households are asked about whether they are more or less poor than in 2000. Using this information, we define the dependent variable as 1 if the household declares that it is poorer in 2006 than it was in 2000, and zero otherwise. 44% of households said they perceived themselves poorer in 2006 than in 2000 (see Table 1).

2.2 Tropical Storm Stan and Precipitation Data

The main question of this research is to assess whether those who were affected by Tropical Storm Stan have a higher likelihood of declaring themselves poorer in 2006 than in 2000. In the 2006 ENCOVI, households were also explicitly asked whether Stan had affected them. Around 23.5% of the households in Guatemala declared they suffered some kind of loss or damage due to the storm.

We use the following criteria to classify municipalities as affected by the storm. The information was obtained from a report commissioned by the "Secretaría Nacional de Planificación y Programación." In the sample, 39.6% of the households lived in municipalities considered affected. So, 60.4% of the households live in municipalities that were not considered affected. Also, within the affected municipalities, there are people who declared that they were not affected. They represent only 25.7% within the affected municipalities, which implies that

74.3% of the households in affected municipalities declared that they were affected by Stan (see Table 1).

Climatic information on precipitation was collected from Climate Forecasting System Reanalysis (CFSR) from simulation of the daily meteorological forecasting worldwide done by the National Centers for Environmental Prediction (NCEP) (Saha et al. 2010). The average precipitation for each municipality for the period when Stan affected them was calculated for each municipality. We also calculate the accumulated typical precipitation before Stan for the same period of the year that Stan hit (from September 28th to October 8th). We find that precipitation significantly increased during Stan, as expected.

2.3 Poor versus Non-poor Municipalities

According to the 2002 Census, the national poverty rate was 55%. Within the poorer 50% of municipalities in 2002, the average poverty rate was 79%. Within the 50% less poor municipalities, poverty rates were also high, reaching an average of 41%. As can be seen in Table 1, a higher fraction of indigenous people live in poor municipalities. Additionally, poor municipalities are less densely populated and the most important economic sectors are agriculture and fishing. These differences are statistically significant.

As also shown in Table 1, households in less poor municipalities declare being poorer in 2006 (46%) than they were in 2000 more often than households in poor municipalities (39%). These differences are statistically significant. It is important to emphasize that poverty rates capture poverty at one moment in time, while our dependent variable, being poorer in 2006 than in 2000, captures change.

The likelihood of reporting being affected by Stan is larger in poor municipalities (26.58%) than in less poor municipalities (21.7%). This shows that poor municipalities were more exposed to Stan. This is consistent with the increases in precipitation shown in the period and the fact that they depend more on agriculture and fishing. These differences are also statistically significant. However, the percentage of households in the sample that live in affected municipalities is larger in less poor municipalities. This might be explained by differences in populations between affected and unaffected, and poor and less poor, municipalities.

Within affected municipalities, the percentage of households that declared that they were not affected by Stan is significantly lower in poor municipalities than in less poor municipalities. This also shows that Stan affected a larger percentage of households in poor municipalities than in less poor municipalities, among the municipalities considered affected.

2.4 Control Variables

From the 2006 ENCOVI survey, we also obtained demographic variables for the head of household, such as sex, age, level of education, and migration between 2000 and 2006. The number of dependents in the household (people younger than 12 years) was also included. In Table 1, we show that the differences between poor and less poor municipalities are significant for every characteristic we use in the analysis.

Additionally, from the census, we have information about other socioeconomic conditions at the municipality level for 2002. This allows us to control for initial socioeconomic conditions at the aggregate level. Variables included at the municipality level were the percentage of indigenous population and percentage of population in agriculture and fishing. In Table 1, we can see that differences between poor and less poor municipalities are significant for every characteristic we use in the analysis.

3. Empirical Strategy

In order to identify the effects of Stan on the likelihood of being poorer in 2006, we face two challenges. The first challenge is identifying which households have been affected by the storm. As explained before, studies that rely on self-reporting and use households that do not report being affected as controls fail to account for the indirect effects of shocks. For instance, impacts on infrastructure and the economy could indirectly negatively affect those individuals within the community by, for example, reducing economic activity. However, when a shock occurs, governments could also increase expenditures in relief efforts through social programs and public investments in the areas affected (Cole et al. 2012; Besley and Burgess 2002). Households that live in affected areas but were not affected could be better off than they would have been if the shock had not occurred. As for papers that use municipality level data to identify shocks, many of these studies relied on climatic information (as in Vicarelli 2010; Macours et al. 2012), with the result that households that were not directly affected by the shock, living in affected municipalities, are classified as affected.[1] As argued before, the level of impacts varies among those indirectly affected, with some households better off due to the public investments that follow the shock, and others worse off due to reduced economic activity. Distinguishing these effects is not possible when using only municipality level data. For the reasons discussed

[1] Similarly, de Janvry et al. (2006) use self-reported information but aggregate these reports at the community level for the statistical analysis.

above, this issue might be even more important when estimating the differences in the effects between poor and less poor households, especially if relief efforts are being targeted based on poverty.

We address this issue using a combination of self-reported data and municipality level data. In Table 2, we classified households according to whether or not they live in a municipality declared affected and whether or not they declared that they were affected. In Table 2, we show households that reported being affected and that live in a municipality that was declared affected (cell A), households that reported not being affected but live in a municipality that was declared affected (cell B), households that reported being affected but live in a municipality that was declared not affected (cell C), and households that reported not being affected and live in a municipality that was declared not affected (cell D).

If we compared treated and controls using aggregated data (A and B versus C and D), we would conclude that the effect is about a 4% increase in the likelihood of becoming poorer, while, if we compared treated and controls using only self-reported data (A and C versus B and D), we would conclude that the effect is about a 5% increase in the likelihood of becoming poorer. However, those estimates are contaminated by observations in B. In the case of aggregated data, observations in B affect the set of treated observations by reducing treated average outcome levels. In the case of self-reported data, observations in B affect the set of control observations by increasing control average outcome levels. A better estimate of the effect would come from using only observations that were fully affected (cell A) versus observations that were not affected in any form (cell D). We then would conclude that the effect is about a 9% increase in the likelihood of becoming poorer.

We can see that, on average for the whole sample and using only aggregated data or only self-reported data, households in B reduce the estimates of the impact. However, the direction of the sign by which B can affect the estimations is uncertain and might vary depending on the sub-sample analyzed. As we explained previously, households in B might be better or worse off after the shock. In Table 3, we show how the values of B change drastically between poor municipalities and less poor municipalities.

Moreover, we can estimate whether Stan and all its consequences had positive or negative indirect effects on those households in cell B (those that declared themselves unaffected in affected municipalities) by comparing outcomes in B against outcomes in D. We observe that individuals in B in less poor municipalities might be worse off. However, individuals in B in poor municipalities might be better off.

Comparing outcomes of these groups, however, might not be free of bias. The second challenge we face is that there might be other variables that are correlated with being affected by Stan and also with becoming poorer. In order to address this issue, we use regression analysis to estimate the two effects of Stan on the perceived likelihood of being poorer in 2006 compared to 2000. The first is the direct effect, and the regression equation is:

$$SE_{ij} = f(\beta_1 S_{ij} + \beta_2 PM_j S_{ij} + \sum_{l=1}^{L} \delta_l X_{il} + \sum_{k=1}^{K} \alpha_k Z_{ijk} + u_i)$$

where SE_{ij} is the dependent variable, the perceived socioeconomic outcome of household *i* in 2006 compared to 2000; S represents a dummy variable that takes the value of 1 if household *i* in municipality *j* was directly affected by Stan or 0 if household *i* was located in municipality *j* that was not affected by Stan; PM_j is a dummy variable indicating whether municipality *j* was poor; X_{ik} are *l* characteristics of household *i*; and Z_{ijk} are *k* variables of municipality *j* for household *i*. When measuring the direct effects, we eliminate from the analysis those households that described themselves as unaffected, even though they were located in municipalities that were affected (households in B), and those that described themselves as affected, even though they were in municipalities that were not declared affected (households in C).

We test whether the effects vary by municipality poverty levels. The effect of Stan on non-poor municipalities is captured by β_1, while the storm's effect on poor municipalities is captured by $\beta_1 + \beta_2$. Therefore, the difference between the effects of Stan in poor municipalities and in non-poor municipalities is captured by β_2. If β_2 is positive, poor municipalities were more affected by Stan than were non-poor municipalities.

The coefficient β_2 will be biased if there is correlation between u_i and $PM_j S_{ij}$. For example, households affected by Stan in poor municipalities might have been affected by another unobservable factor that did not affect the rest of the observations. If this is the case, β_2 will capture not only the difference in the effects of the shock between poor and non-poor municipalities, but also the effects of that unobservable factor. However, we control for a series of households and municipality characteristics.

As we mentioned before, we eliminate from the analysis observations that could have been indirectly affected by the storm. If the storm affected those observations (whether positively or negatively), the inclusion of those observations would bias the estimated coefficient of the shock, β_1. If the indirect effects are large, bias will be large when including these observations in the analysis.

Moreover, if the indirect effects vary in magnitude between poor and non-poor municipalities, the estimation of the coefficient β_2 will also be biased. For instance, due to the storm, low-skilled workers from poor municipalities that were not directly affected by the storm might be hired for reconstruction and might end up being better off than if the storm had not occurred. If the indirect effects are positive (adverse effects) in non-poor municipalities, the estimated effect of the shock in these municipalities will be estimated lower than it actually is. If the indirect effects are negative (beneficial effects) in poor municipalities, the estimated effect of the shock in these municipalities will be estimated higher than it actually is, and β_2 will be biased upward by the inclusion of these observation in the analysis.

In fact, indirect effects could be estimated with:

$$SE_{ij} = f(\beta_1^{ID} S_{ij}^{ID} + \beta_2^{ID} PM_j S_{ij}^{ID} + \sum_{l=1}^{L} \delta_l X_{il} + \sum_{k=1}^{K} \alpha_k Z_{ijk} + u_i)$$

by defining S_{ij}^{ID} as 1 if household i declared itself unaffected but was located in a municipality j that was affected. Households that reported being affected by Stan would be dropped when estimating indirect effects. If β_1^{ID} and β_2^{ID} are significant, it would imply that including households that were located in affected municipalities but reported not being affected would bias the estimated direct effects. We show that this is the case in Guatemala.

4. Results

4.1 Direct Impacts

We estimate the direct impact of Stan on the probability of being poorer in 2006 relative to 2000 for those households that reported having been affected by the storm. We present these results for five different specifications (see Table 3): without any controls (Column 1), controlling only for household characteristics (Column 2), controlling for household and municipality characteristics (Column 3), and controlling additionally for precipitation during Stan (Columns 4 and 5). The effect was estimated for two groups: households located in poor municipalities and households located in non-poor municipalities.

We consistently observe that Stan increased the probability of worsening the economic situation in both groups for all five specifications shown in Table 3, Panel A. For those affected by Stan in non-poor municipalities, the probability of reporting a worse situation increases by estimated magnitudes that range from 7.51% to 10.84%. For those affected by Stan in poor

municipalities, the estimates of the effects range from 2.4% to 3%, but most are not statistically significant. Non-poor municipalities are significantly more affected than poor municipalities, as can be seen in the last row of Panel A.

4.2 Biased Estimates

As discussed in the empirical section, if we had included households that reported not being affected, despite being located in affected areas, the estimates would have been different (see Table 3, Panel B). For non-poor municipalities, coefficients tend to be slightly lower, ranging from 5.9% to 7.8%. For poor municipalities, the estimated effects are now positive and significant, ranging from 3.6% to 5.1%. The differences between poor and non-poor municipalities become insignificant.

If we had defined all households in affected municipalities as directly affected by the storm, the estimates would also have been different (see Table 3, Panel C). For non-poor municipalities, coefficients are also slightly lower, ranging from 6.4% to 9.3%. For poor municipalities, however, the coefficients are insignificant and some of them become negative. These results are slightly lower than the ones found in Panel A. However, these treatment effects include households that were affected indirectly and these effects could be positive or negative. The differences between poor and non-poor municipalities become significant, as can be seen in the last row of Panel C.

4.3 Indirect Effects

To complement the analysis, we estimated indirect effects of Stan (see Table 3, Panel D). We test whether those individuals in affected zones that reported not being affected were actually affected. We find that, for non-poor municipalities, those households that live in affected municipalities, but reported not being affected directly, have a higher probability of reporting a worse situation. The estimates of the increment in that probability range from 4.3% to 6.4%. These results are all statistically significant. This is consistent with our previous discussion about the fact that including these observations will likely bias the coefficients downward.

However, in poor municipalities, the opposite occurs. Those individuals in households that were not affected, in municipalities that were affected, were better off after the occurrence of the event. The probability of reporting a worst situation decreases. This reduction ranges from 3.29% to 5.63%. The government might have increased anti-poverty programs in the places that were hit by the storm. Reconstruction efforts might especially benefit the poor because the demand for low-skilled labor increases. Whatever the reason for this finding, it is important to

emphasize that the inclusion of indirectly affected households as if they were not affected will bias the estimates of the impacts, as shown in Table 3, Panels B and C. The difference between the impacts in poor and non-poor municipalities will also be biased.

4.4 Agricultural Intensity and Gender Differences

We then split the sample of municipalities according to the intensity in agriculture[2] and by the head of household's gender. We find that, in agricultural municipalities, there is no statistically significant difference between the direct effects on households living in poor and non-poor municipalities (see Table 4). This result holds when we use the entire sample and when we use only male or female heads of households. The magnitudes of these effects are similar for households living in both poor and non-poor agricultural municipalities when using the entire sample and when focusing on households headed by males. For households headed by females, the impact seems to be larger for those living in poor municipalities; however, the effect is not statistically significant.

We also find that the direct effects differ significantly in non-agricultural municipalities between poor and non-poor municipalities. Households in poorer municipalities are significantly less affected. This might be the result of government assistance that is targeting the poor. This could also be explained by the fact that households in poor municipalities have few assets and little to lose. These results were robust to head of household gender.

In non-poor municipalities, the indirect effects of Stan on the likelihood of reporting becoming poorer were positive and significant, especially in agricultural municipalities (see Table 5). The magnitude of the adverse effects in poor agricultural municipalities was also positive and significant. However, the indirect effects of Stan in poor and non-agricultural municipalities were negative and significant. Households that were in an affected municipality but reported not being affected by the shock are significantly better off than they would have been if the shock had not occurred.

[2] We use the 2002 census information about individuals' economic activity. The median is 63% participation in agriculture. If 63% or more of the individuals in a municipality work in agriculture, the municipality is classified as an agricultural municipality; if less than 63% work in agriculture, the municipality is classified as a non-agricultural municipality.

5. Conclusions

Extreme weather events have increased in intensity and frequency. The literature analyzing the effects of these events on social and economic outcomes has increased significantly. Most previous analyses use either self-reported data about being affected, or aggregated data such as precipitation at the municipality level. In this paper, we argue that these estimates might be biased due to the presence of indirect effects. In studies that use self-reported data, households indirectly affected are used as controls, while in aggregated level data, households indirectly affected are part of the treated observations.

Using data for Guatemala, we estimated separately the direct and indirect effects of Tropical Storm Stan on subjective economic well-being. We found that households that were directly affected by Stan have a significantly higher likelihood of reporting being poorer after the event. We also found that the indirect effects can be positive or negative. For non-poor municipalities, households that reported being unaffected by the storm, despite living in an affected municipality, have a significantly higher likelihood of reporting being poorer in 2006 relative to 2000. For poor municipalities, households that reported not being affected by the storm, despite living in an affected municipality, have a significantly lower likelihood of reporting being poorer in 2006 relative to 2000. This might be explained, for instance, by the redirection of government resources toward poorer affected communities.

Given that shocks and responses to shocks will likely affect households not directly exposed, estimates of the effects of extreme weather events on social outcomes are difficult to measure. Without considering exposure data at both household level and municipality level simultaneously, estimates of impacts might be biased because they will capture the effects of responses to shocks over the population.

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Tables

Table 1: Descriptive Statistics of Household Characteristics

Variables	**All sample**	Non-Poor Municipalities	Poor Municipalities	Difference	
Dependent variable					
Perceived likelihood of being poorer(f)	0,44	0,46	0,39	6,52	***
Independent variables					
Variables of interest					
HH affected by Stan self-report (%)	23,52	21,70	26,58	4,87	***
HH in municipalities affected by Stan (%)	39,59	41,18	36,88	4,30	***
HH not affected in municipalities affected by Stan (%)	25,77	28,49	21,14	7,35	***
Precipitation during Stan[a]	317,93	300,72	347,13	46,40	***
Precipitation before Stan[b]	189,92	185,14	198,02	12,87	***
Control variables					
HH control variables					
Household characteristics					
Members younger than 12	1,61	1,37	2,01	0,63	***
Urban	42,25	52,67	24,55	28,12	***
Head of household characteristics					
Men (%)	78,77	77,80	80,40	2,60	***
Age (years)	45,51	45,74	45,11	0,63	**
Spanish speaking[c] (%)	71,92	86,27	47,56	38,71	***
Migrate 2001-2006 (%)	4,25	5,21	2,60	2,60	***
No education (%)	33,53	26,29	45,81	19,51	***
Primary (%)	48,04	49,75	45,13	4,62	***
More than primary (%)	18,43	23,94	9,05	14,89	***
Municipality control variables					
Population density (# people per Km^2)	484,64	660,88	185,40	475,48	***
Indigenous population (%)	36,10	20,62	62,37	41,75	***
Poverty (%)	55,66	41,65	79,43	37,78	***
Extreme poverty (%)	15,28	7,31	28,78	21,46	***
Economic sector (%):					
Agriculture and fishing	50,18	39,68	67,99	28,30	***
Others	49,82	60,31	32,00	28,30	***
Observation number	13.438	8.457	4.981		
Number of counties	288	149	139		

*,**,*** indicate significance at 10%, 5%, and 1%, respectively.

HH: Households, f: fraction.
a/ Accumulated rain from September 28 to October 10 in year 2005; b/ Accumulated rain from September 28 to October 10 in year 2004; c/ As opposed to people speaking indigenous dialects
Poverty threshold of municipalities: 67.34% (median of poverty of 11th Population Census 2002)

Table 2: Households and Municipalities Affected by Stan

Total		Household reported as affected	Household reported as not affected	Using aggregated data
Affected municipality		**A**	**B**	Treated
	Observations	1857	3463	5320
	Likelihood of being poor	0,5	0,43	0,46
Unaffected municipality		**C**	**D**	Controls
	Observations	1303	6815	8118
	Likelihood of being poor	0,42	0,41	0,42
Using household level "self-report" data		Treated	Controls	
	Observations	3160	10278	
	Likelihood of being poor	0,47	0,42	

Table 3: Estimates of the Direct and Indirect Impact of Stan on the Likelihood of Being Poorer in 2006 With Respect to 2000, by Poverty of Municipality

Column	1	2	3	4	5
Effect of Stan					
Panel A: Direct effects					
All Municipalities	0.0542***	0.0538***	0.0569***	0.0772***	0.0780***
Non-poor Municipalities	0.0751***	0.0845***	0.0932***	0.1084***	0.1083***
Poor Municipalities	0.0281*	0,024	0,0153	0,0291	0,0302
Difference	0.0470**	0.0605***	0.0779***	0.0793***	0.0780***
Panel B: Direct effects using contaminated controls					
All Municipalities	0.0480***	0.0505***	0.0542***	0.0667***	0.0665***
Non-poor Municipalities	0.0594***	0.0664***	0.0722***	0.0781***	0.0745***
Poor Municipalities	0.0418***	0.0368**	0.0384**	0.0516***	0.0511***
Difference	0,0176	0,0296	0,0337	0,0264	0,0234
Panel C: Direct effects using as treatment the whole municipality					
All Municipalities	0.0416***	0.0374***	0.0381***	0.0576***	0.0591***
Non-poor Municipalities	0.0642***	0.0681***	0.0775***	0.0938***	0.0936***
Poor Municipalities	-0,0048	-0,0095	-0,0187	-0,0048	0,0001
Difference	0.0690***	0.0776***	0.0961***	0.0986***	0.0935***
Panel D: Indirect effects: Not affected HH in an affected municipality					
All Municipalities	0.0183*	0,0094	0,0049	0.0237**	0.0272**
Non-poor Municipalities	0.0431***	0.0413***	0.0451***	0.0615***	0.0640***
Poor Municipalities	-0.0474***	-0.0506***	-0.0563***	-0.0387**	-0,0329
Difference	0.0906***	0.0919***	0.1014***	0.1001***	0.0969***
Control Variables					
Household control variables	No	Yes	Yes	Yes	Yes
Municipality control variables	No	No	Yes	Yes	Yes
Precipitation during Stan	No	No	No	Yes	Yes
Square of Precipitation during Stan	No	No	No	No	Yes

Notes: *,**,*** indicate significance at 10%, 5%, and 1% respectively.
HH: Households
Poverty threshold of municipalities: 67.34% (median of poverty of 11th Population Census 2002)
See the list of household control variables and municipality control variables in Table 1.

Table 4: Estimates of the Direct Impact of Stan on the Likelihood of Being Poorer in 2006 with Respect to 2000, by Sex, Poverty[1], Economic Activity[2] and Region

	All	Non-poor municipalities	Poor municipalities	Difference
Overall Effect	0.0780***	0.1083***	0.0302	0.0780***
By agricultural Intensity				
Agricultural municipalities	0.1007***	0.0875**	0.0862***	0.0013
Non-agricultural municipalities	0.0708***	0.1106***	-0.0222	0.1328***
Male head of household	0.0770***	0.1098***	0.0290	0.0808***
By agricultural Intensity				
Agricultural municipalities	0.0975***	0.1036**	0.0802***	0.0234
Non-agricultural municipalities	0.0688***	0.1099***	-0.0082	0.1181***
Female head of household	0.0747***	0.0964***	0.0363	0.0602
By agricultural Intensity				
Agricultural municipalities	0.1096**	0.0228	0.1148**	-0.0920
Non-agricultural municipalities	0.0641*	0.1057***	-0.0741	0.1798**

Notes: *,**,*** indicate significance at 10%, 5%, and 1%, respectively.
1/Poverty threshold of municipalities: 67.34% (median of poverty of 11th Population Census 2002)
2/Agricultural threshold of municipalities: 62.05% (median of percentage of economically active population in the agricultural sector. 11th Population Census 2002)
We controlled by household, municipality and precipitation variables.

Table 5: Estimates of the Indirect Impact of Being in Affected Municipalities on the Likelihood of Being Poorer in 2006 with Respect to 2000, by Sex, Poverty[1] and Economic Activity[2]

	All	Non-poor municipalities	Poor municipalities	Difference
Overall Effect	0.0272**	0.0640***	-0.0329	0.0969***
By agricultural Intensity				
Agricultural municipalities	0.0673***	0.1131**	0.0613**	0.0518
Non-agricultural municipalities	-0.0025	0.0622***	-0.1625***	0.2246***
Male sample	0.0268*	0.0652***	-0.0400*	0.1052***
By agricultural Intensity				
Agricultural municipalities	0.0660**	0.1438***	0.0567*	0.0872
Non-agricultural municipalities	-0.0033	0.0589***	-0.1634***	0.2223***
Female sample	0.0215	0.0562	-0.0050	0.0612
By agricultural Intensity				
Agricultural municipalities	0.0677	0.0258	0.0788	-0.0530
Non-agricultural municipalities	-0.0086	0.0685*	-0.1650**	0.2334***

Notes: *,**,*** indicate significance at 10%, 5%, and 1%, respectively.
1/Poverty threshold of municipalities: 67.34% (median of poverty of 11th Population Census 2002).
2/Agricultural threshold of municipalities: 62.05% (median of percentage of economically active population in the agricultural sector. 11th Population Census 2002).
We controlled by household, municipality and precipitation variables.