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Disquiet on the Weather Front

The Welfare Impacts of Climatic Variability in the Rural Philippines

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Abstract

Three recent rounds (2003, 2006, and 2009) of the Family Income and Expenditure Survey are matched to rainfall data from 43 rainfall stations in the Philippines to quantify the extent to which unusual weather has any negative effects on the consumption of Filipino households. It is found that negative rainfall shocks decrease consumption, in particular food consumption. Rainfall below one standard deviation of its long-run average causes food consumption to decrease by about 4 percent, when compared with rainfall within one standard deviation. Positive deviations above one standard deviation have a limited impact. Moreover, for households close to a highway or to a fixed-line phone, consumption appears to be fully protected from the impact of negative rainfall shocks.

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Disquiet on the Weather Front:
The Welfare Impacts of Climatic Variability in the Rural Philippines

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Introduction

While there is a great deal of uncertainty over the exact magnitudes of the global changes in temperature and precipitation, it is widely accepted that significant deviations of the variability of climate from its historical patterns are likely to occur (IPCC, 2007).[1] Considering that millions of poor households in rural areas all over the world are dependent on agriculture, there are increasing concerns that the change in the patterns of climatic variability is likely to add to the already high vulnerability of households in rural areas of developing countries, thus posing a serious challenge to development efforts all over the world. In view of this impending threat of climate change upon the poor, it is critical to have a deeper understanding of the household adaptation strategies and targeted measures that could mitigate the poverty impacts of erratic weather.

With 60% of its population living in coastal areas, sensitivity to the El Niño phenomenon and a location which makes it prone to typhoons, the Philippines is one of the countries with the highest exposure to climate change risks. It is among the top 10 countries worldwide at risk for both climate change and disasters.[2] Forecasts on climate change predict an increase in average annual precipitation for the Philippines, coupled with an increase in variability within the year, with wetter wet seasons and dryer dry seasons.

Understandably, given their disruptive and destructive power, typhoons attract a lot of attention in the Philippines. It is estimated that 0.5% of GDP is lost to natural disasters each year. This figure is expected to increase to 1 or 2% due to climate change. In the recent past, a typhoon hit the Philippines in the first week of September 2006, in the last week of November 2006, and in the third week of June 2008. In September and October 2009, two typhoons, Ondoy and Pepeng, are estimated to have cost the Philippines economy 2.7% of GDP (Philippines PDNA, 2009).

The welfare impacts of extreme weather events and natural disasters, though rather infrequent, can be easily appreciated since they are very visible. From a policy perspective, if a typhoon destroys homes and displaces populations, the action required is to rebuild the houses and the basic infrastructure that was destroyed. On the contrary, it is way more difficult to assess the welfare impacts of deviations in rainfall from normal patterns that are typically more frequent and of smaller magnitude. What evidence is there on the extent to which smaller and more frequent weather shocks impact on household living standards in the Philippines and what is the scope for public intervention?

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[1] According to the Intergovernmental Panel on Climate Change (IPCC) a narrow definition of climate refers to the statistical description in terms of the mean and variability of quantities such as temperature, precipitation and wind over a period of time ranging from months to thousands of years. The norm is 30 years as defined by the World Meteorological Organization (WMO). Climate is different from weather which refers to atmospheric conditions in a given place at a specific time. The term "climate change" is used to indicate a significant variation (in a statistical sense) in either the mean state of the climate or in its variability for an extended period of time, usually decades or longer (Wilkinson 2006).

[2] The impacts of climate change on Philippines are summarized in the recent document "A Strategic Approach to Climate Change in the Philippines" by the Sustainable Department of the EAP region.

With these considerations in mind, in this paper, we carry out an analysis of the welfare impacts of climatic variability in the rural areas of the Philippines. One of the main objectives of our study is to quantify the extent to which unusual or erratic weather has any negative impacts on the welfare of Filipino households. Erratic weather may affect agricultural productivity which, depending on how effective was the portfolio of *ex ante* and *ex post* risk management strategies employed, may translate into reduced income and reduced food availability at the household level. Based on historical experience and the multiplicity of economic and institutional constraints faced, rural households in the Philippines, as most rural households all over the world, have managed to develop traditional strategies for managing climatic risk. For example, households may undertake *ex-ante* income-smoothing strategies and select a diversified portfolio of occupations across its adult members that guarantee a minimum level of consumption (Menon, 2009) or adopt low return-low risk crop portfolios (Rosenzweig and Binswanger, 1993). Furthermore, households may use their savings (Paxson, 1992), take loans from the formal financial sector to carry them through the difficult times (Udry, 1994), sell assets (Deaton, 1992), or send their children to work instead of school in order to supplement income (Jacoby and Skoufias, 1997). Additional strategies include the management of income risk through *ex-post* adjustments in labor supply such as multiple job holding, and engaging in other informal economic activities (Morduch, 1995; Kochar, 1988).[3]

Yet, quantitative evidence on how successful such risk management strategies are at protecting household welfare from weather-related shocks in the Philippines is quite scarce.[4] To the extent that the current risk-coping mechanisms are not very effective in protecting welfare from erratic weather patterns one can be quite certain that the change in the patterns of climatic variability associated with climate change is likely to reduce the effectiveness of the current coping mechanisms even more and thus increase household vulnerability further.

Our analysis relies on three recent rounds (2003, 2006 and 2009) of the Family Income and Expenditure Survey, a nationally representative survey of approximately 22,000 (different) households surveyed per round. We match the survey to rainfall data from 43 rainfall stations in the Philippines. For our purposes, it is of interest to note that there was substantial variation in rainfall over the period, with 2002 being a year with some drought and 2008 being a year with rather high rainfall.

There is some evidence of the impact of weather shocks on consumption. Microsimulation exercises estimate that 0.9 points of Philippines GDP were lost to El Niño Southern Oscillation (ENSO) in 2010 (Narayan et al., 2010). In the same set of estimates, it is found

[3] There are other channels through which weather may affect the wellbeing of individuals. For example, the changes in climate may increase (or decrease) the prevalence of certain diseases and thus have impacts on health outcomes. Skoufias and Vinha (2011) for example, explore the impacts of weather shocks on the height for age of children less than three years of age in rural Mexico.

[4] Other studies relying on self-reported incidence of different types of shocks, such as floods, droughts, freeze, fires and hurricanes include Garcia Verdu (2002), Skoufias (2007) and de la Fuente (2010). None of these earlier studies, however, use actual meteorological data.

that, contrary to its impact on GDP, the impact of ENSO on poverty is small, increasing it by *only* 0.4 percentage points. An earlier study also found an impact of ENSO on the incidence of poverty (Datt and Hoogeveen, 2003). However, the measure of the shock is not satisfactory since it is reported by the household itself. Yang and Choi (2007) is the closest study to ours. The authors provide evidence that rainfall shocks decrease household expenditures and they also find that remittances are used as insurance: in migrant households, consumption is not impacted by income (where income is instrumented with rainfall shocks), while in non-migrant households, a 10% decrease in income leads to a 5% decrease in consumption. One concern with these estimates, however, is that consumption and income are not comparable in the two surveys they use. In addition, their analysis does not distinguish between urban and rural areas. Our estimates allow more sizable variation of the shock since we use a larger cross-section in rural areas and have 3 rounds of the data, allowing more variation of the shock over time.

As shown by Yang and Choi (2007) with remittances, the distribution of welfare losses associated with weather shocks depends on the determinants of household and community level vulnerability. The geography of the Philippines represents huge challenges in terms of communication, transport and access to social services. These challenges are likely to become more acute with climate change. Understanding the distribution of the impact of rainfall shocks across the regions of the Philippines as well as examining which community or municipality level factors modify the impact of weather shocks plays an important role in designing policies to minimize exposure to and the impact of these shocks.

Hence, we examine the distribution of the impact of weather shocks. The impact of climate change is predicted to differ across the regions of the Philippines, with increased rainfall in the areas of Central Visayas, Southern Tagalog, Luzon, Samar, and the central and western parts of Mindanao while a decrease in rainfall is expected in northern and eastern Mindanao and parts of western Luzon (World Bank, 2010). Given the geography of the Philippines and the high incidence of poverty, well designed and targeted policies necessitate knowledge of the distribution of rainfall impact: both across regions and across the level of income.

A second objective of our study is to shed some light on the types of policies that help communities and households adapt to rainfall shocks. Weather shocks are aggregate shocks by nature, affecting at least a whole community, if not a whole region or country. While there may be variation in the way individual households are affected, depending on the type of activities they conduct or their sources of income, it is important to identify what types of policy-related actions that are associated with a smaller adverse impact at the community and/or at the household level. For example, what are the household and community characteristics that help households mitigate the impact of shocks? Is it better connectivity in terms of better access to communication or transportation networks that link an affected community to other communities less hard hit? [5]

[5] Datt and Hoogeveen (2003) interact their measure of El Niño shock with community characteristics but do not find any significant effect of infrastructure helping smooth the El Niño shock on household consumption. Their study was conducted using 1998 data. Does their result hold with different and more recent data?

We find that negative rainfall shocks decrease consumption, and in particular food consumption. Rainfall below one standard deviation of its long-run average causes food consumption to decrease by about 4%, when compared to rainfall within one standard deviation. On the other hand, positive deviations above one standard deviation have a limited impact. For food consumption, the impact is about 1% and it is not significant. For total expenditure, the impact is about 2% and not robust. The difference between the two shocks is not always significant. Put differently, in the case of total consumption good years seem either not to compensate for bad years or they compensate in a limited way. In the case of food consumption, losses during bad years are not compensated at all during good years. Hence, if shocks increase with climate change, household basic needs in the form of food consumption will decrease. While we do not have direct evidence, the evidence seems to point to an impact of shocks through prices as much as through nominal income. What is encouraging for public policy is that access to communication infrastructure, as well as to markets, seems to decrease the impact of negative shocks, making them nil for those households that are close to a highway or to a fixed line phone. On the other hand, increased diversification of activities does not seem to be particularly helpful with respect to shocks. Hence, interventions that help improve communication and access to markets are likely to help households through maintaining food supply chains and helping keeping food prices from increasing as a result of local rainfall shocks.

In the next section we briefly review the literature and outline how rainfall shocks affect consumption. We then present the data and some summary statistics in section 3. The results are in section 4 while section 5 concludes.

Framework

Rainfall mainly affects consumption through its impact on real income. Agricultural income is likely to be the most sensitive to the environment, with the marginal productivity of labor being affected by rainfall shocks, affecting the profits of farmers as well as the wages of agricultural wage workers. In the Philippines, studies have documented the adverse effect of drought due to ENSO on rice production (Dawe et al., 2009; Roberts et al., 2009). Besides its effect on nominal income, rainfall is also likely to affect real income through its impact on the prices of agricultural commodities. If bad rainfall decreases rice production, then the price of rice may increase. This may hurt non-agricultural households. At the same time, an increase in rice prices may slightly weaken the adverse effect of the drought on net rice producers, although the overall effect is likely to still be negative for them. Lastly, rainfall shocks may also affect non-agricultural households through general equilibrium effects.

Irrespective of the channel at work, the impact of rainfall comes with a lag. Income from farming is only collected after harvest. Similarly, prices changes due to bumper or poor harvests typically soon after the harvest. General equilibrium effects are also likely to come with a lag. An exception may be the income of agricultural wage workers whose wages or labor demand may be affected earlier by rainfall shocks (Jayachandran, 2006).

Depending on the household's ability to cope with income fluctuations, a negative income shock brought on by bad weather may translate into a reduction in consumption (Jacoby and Skoufias, 1998; Dercon and Krishnan, 2000). In theory, weather-related shocks are difficult to insure against because they affect a whole community, decreasing the ability to use informal risk-sharing within the community. However, households may be able to protect their basic needs from the adverse shock. It has been found for instance that food consumption is better insured than non-food consumption (Skoufias and Quisumbing, 2005).

Beyond the ability of households to cope with whether shocks, a stronger case could be made about the likely impacts of climate change on household welfare, if it were possible to establish that the relationship between rainfall shocks and consumption is non-linear. Weather–related shocks are predicted to take place more frequently because of climate change. This, however, does not imply that climate change and increased climatic variability is likely to have an overall negative effect on welfare. This is, because it is possible that the welfare benefits associated with positive shocks, such as the better crop yields associated with slightly more than normal rainfall, on average may "cancel out" the adverse effects of negative shocks. Thus, in this case where the relation between shocks and welfare is "linear", on average, climate change may not have an impact on household welfare. On the contrary, climate change will have an impact on average, if, for example, negative shocks have a negative welfare impact that is larger, in absolute value, than the positive welfare impact of positive shocks. If this is the case, then there is need for action to protect households from negative shocks due to climate change. We illustrate this in figure 1.

Figure 1 here

The grey dotted line shows a case where shocks have an impact that is linear: positive shocks and negative shocks have impacts of similar magnitude. The black dashed line represents a different case: negative shocks have an impact, of the same magnitude as that in the grey dotted line but positive shocks have no impact. With the linear impact –the grey dotted line - clearly the average of positive and negative shocks of similar magnitude will be zero. With the black dashed line however, the average of positive and negative shocks is negative and this is the case where climate change may be harmful for consumption.

Data and Descriptive Statistics

We use the 2003, 2006 and 2009 waves of the Family and Income Survey (FIES). The FIES is conducted by the Filipino Statistical Office and is regionally representative. The three rounds are conducted in the same time in the year and the same consumption module was used in all three rounds, allowing for comparability across the surveys.

We merge the FIES with data built using the monthly rainfall records of 43 rainfall stations across the Philippines, obtained from the Philippines Atmospheric, Geophysical and Astronomical Services Administration (PAGASA). Figure 2 displays the location of the 43

rainfall stations throughout the country, whereas Figure 3 presents the average or normal amount of rainfall (in mm) in each province over the years 1951 to 2009.

Figures 2 and 3 here

For our analysis, each household in a municipality is assigned the closest rainfall station to the municipality where it resides; conditional on the fact that the station is on the same island as the municipality.[6] In order to improve accuracy, we could use the average of the three closest stations rather than a single station. However, smaller islands only have one rainfall station. Thus, we choose to use the rainfall from the closest rainfall station in order to have a uniform methodology for all the municipalities. In some cases where a municipality comprises several islands, we cannot identify which households in the municipality are on the same island as the rainfall station. We have variables flagging this case as well as a variable flagging municipalities which do not have a rainfall station in the same island. We also conduct robustness checks by excluding municipalities where rainfall is measured with less precision.

We use per capita consumption as a measure of household welfare for both conceptual and pragmatic reasons. First, consumption due to smoothing tends to fluctuate less in the short term than income, which can be affected by the seasonality of employment. Consumption expenditures reflect not only what a household is able to command based on its current income including transfers, but also whether the household can access credit markets or household savings at times when current incomes are low or even negative. In this way, consumption is thought to provide a better picture of a household's standard of living than a measure of current income. Second, income measures may not accurately capture in-kind, seasonal, or informal income. In particular for poor rural household, total income may be derived from multiple activities with strong seasonal variation and with associated costs that are not always easily assigned. Third, income surveys are susceptible to under-reporting as respondents may perceive incentives to do so. For these reasons, consumption is often considered by economists to provide a more accurate measure of household welfare in less developed countries.

The FIES is conducted in two visits to gather information on income and expenditure over the whole year. The first visit is conducted in July of the survey year covering the period from January 1st to June 30th of the same year. The second visit is conducted in January of the next year gathering information for the period from July 1st to December 31st of the previous calendar year. The FIES data publicly released by the Statistical Office aggregate the data collected over the two visits during the survey year.

There are four climatic zones in the Philippines, with only one zone that has two very pronounced seasons (Luzon, the rice granary of the Philippines is in this zone).[7] Only one other zone has a dry season but it lasts at most three months. In the two remaining climatic

[6] We restrict to stations on the same island because rainfall can change substantially between islands.
[7] A map of the different types of climate in the Philippines can is made available by PAGASA at http://kidlat.pagasa.dost.gov.ph/cab/statfram.htm.

zones, there is no dry season and only one of these two zones has a period with high rainfall. Therefore, in consideration of the fact that there are two cropping seasons for rice and that the FIES captures income and expenditures over the whole year, we choose to simply examine the impact of rainfall deviations from the normal amount of rainfall in the year before the survey. [8]

Thus the initial measure of the rainfall shock is the deviation of average monthly rainfall in a given year from the mean of average monthly rainfall over 1977-2001.[9] Details of data construction are in appendix B. Figure 4 shows the distribution of rainfall shocks in 2002, 2005, 2008, the years before the FIES surveys. The distribution of rainfall varies sizably across the three waves. In particular, 2008 is a year with high rainfall; the median is 34.6 mm, versus -4.5 mm in 2005 and-6.7 mm in 2002. The mean is also much higher in 2008, at 45.8 mm while it is only 3.4 mm and 2.8 mm in 2005 and 2002 respectively. While the medians and the means for 2002 and 2005 are close, the standard deviation is higher in 2005, at 33.8 against 30.9 in 2002. We can see in the figure that the range of values is wider than in 2002.

Figure 4 here

Our analysis is focused on rural *barangays*. A *barangay* is tagged urban if it satisfies any of the following criteria: (i) part of a chartered city or provincial capital with a population density of at least 1,000 persons per square kilometer; (ii) *poblaciones* or central districts of a municipality or city with a population density of at least 500 persons per square kilometer; (iii) there is presence of the following: (a) street pattern or network of streets in either parallel or right angle orientation; (b) at least six economic establishments ; or (c) (commercial banks, manufacturing, recreational, and/or personal services); or (d) at least three social/public establishments (town hall, church, public plaza, park, cemetery, school, hospital, health center, library, market place, or building where trading activities are carried on at least once a week); and (iv) having at least 1,000 residents with occupations predominantly not in farming or fishing.[10]

Sampling. The total sample is 118,832 households. Focusing on rural areas, we have a sample of 65,956 households. In each round the sample is stratified by PSUs that have a probability of selection very close to 1.

[8] In spite of requests, we were unable to obtain the data collected by visit in each year of the FIES survey. This would have allowed us to have a better match between the timing of the rainfall during the year and the date of collection of the household consumption data.

[9] We take average and not total because in 60% of the municipalities, there is at least one month with missing data. Almost half of these, 17%, have only one month with missing data. When taking the average, the denominator is the number of months with non-missing data. This allows not smoothing differences between municipalities due to the availability of data.

[10] The "URB" variable in all three rounds of the FIES (2003, 2006 and 2009) is based on the 2000 urban classification. This classification is updated every time a new barangay census is made available. For our purpose, we held the classification constant for a more consistent comparison across time periods.

Econometric Specification

As mentioned in the discussion, we expect rainfall to have an impact on consumption with a lag. We conduct reduced-form estimates; we examine directly the impact of last year rainfall on consumption:

$$C_{hmt} = \alpha + \beta_P Pdev_{mt-1} + \beta_N Ndev_{mt-1} + X_{hmt} + \gamma_m + \delta_t + u_{hmt} \quad (1)$$

The left hand side variable is the log of real per capita expenditure of household *h* in municipality *m* in year *t*. We also break consumption into food expenditure and non-food expenditure. Details on total and food and nonfood nominal consumption expenditures per capita were deflated over time and across space are provided in appendix B.

The variable $Pdev_{mt-1}$, is a binary variable equal to 1 when rainfall is more than one standard deviation above its long-run average, whereas $Ndev_{mt-1}$, is a binary variable equal to 1 when rainfall is less than one standard deviation below its long-run average.

The omitted category absorbed in the constant term of the regression, denoted by α, is rainfall within one standard deviation of its long run average. As mentioned, an increase in shocks due to climate change will only affect welfare if positive shocks do not compensate for the negative effect of negative shocks. This is why we allow positive and negative deviations to have different coefficients. The reference is what we consider to be the normal, within one standard deviation of the long-run mean.

Table 1

The use of the one standard deviation as the threshold for the definition of a "shock" is based on data constraints. As can be seen in table 1, choosing this threshold is a compromise between having a threshold that actually corresponds to a shock for households and having a shock that occurs frequently enough in our data. A threshold of two standard deviations is not realistic since only 2008 had such a shock, with very high rainfall for one third of the households. We also show results using half a standard deviation as threshold but this threshold seems to be too small to be meaningful for the definition of a shock.

The regression equation estimated also includes municipality fixed effects, denoted by the term γ_m, which allow for time-invariant municipality characteristics. Controlling for municipality fixed effects, removes a considerable amount of heterogeneity between municipalities and make sure that the impact of rainfall shocks on consumption is derived from differences in rainfall across years, within any given municipality. While there is no need for household panel data when examining the impact of weather on consumption, since weather is exogenous to the household, controlling for municipality characteristics seems necessary in order not to capture spurious correlations.[11]

11 Let's take an example where, in a cross section, it happens that rainfall deviation is negative in a municipality which is usually blessed with good weather while rainfall deviation is positive in a municipality

Additional controls used in regression (1) include a set of basic household characteristics such as household size, sex and education of the household head, denoted by the vector X_{hmt}, and a set of binary variable for the year of the survey, denoted by δ_t. The latter controls for aggregate effects, such as economic growth or growth in the real gross domestic product.[12]

Overall, considering the exogeneity of the rainfall shock variable, and given that we control for municipality time-invariant or fixed effects, we are quite confident that our estimates reflect the causal effect of rainfall on household consumption. Controlling for additional characteristics could lead us to include household choices that are determined by weather.

The geographic distribution of the impact of rainfall

Understanding which categories of households are affected by weather shocks will help better target social safety nets to protect households from these shocks. Besides understanding the distribution of the impact of weather shocks, it is important to understand the extent to which households are able to smooth shocks.

We examine in which regions households are most affected by shocks. This is useful to understand the implications of climate change since, as described in the introduction, climate change is likely to differ across regions of the Philippines. We run the regression specified below:

$$C_{hmt} = \alpha + \beta_{\mathrm{P}} Pdev_{mt-1} + \beta_{\mathrm{N}} Ndev_{mt-1}$$
$$+ Z_{\mathrm{R}} * (\alpha + \beta_{\mathrm{P}} Pdev_{mt-1} + \beta_{\mathrm{N}} Ndev_{mt-1}) +$$
$$+ X_{\mathrm{hmt}} + \gamma_m + \delta_t + v_{hmt} \qquad (2)$$

The variables are the same as in equation (1) and Z_{R} is a categorical variable indicating the region of the household residence.

Interaction of the rainfall shock with municipality-level infrastructure and activities

We also analyze the extent to which access to policy related variables such as infrastructure leads to protecting household consumption from negative rainfall shocks. For this purpose, we use module 5 of the population census collecting information on *barangay* infrastructure and other socio-economic characteristics, available for the years 2000 and 2007. Given that the census years do not match the years that FIES is available

which has historically bad weather. If the historic rainfall conditions translate into high consumption levels, then one may find that a negative deviation is associated with a relatively higher level of consumption.

[12] We do include controls for the month of interview because the survey is conducted in the same months across the 3 waves: July for the first visit and January for the second visit.

we merge the 2000 census with the 2003 FIES and the 2007 census with the 2006 and 2009 FIES. However, it is important to bear in mind that many variables regarding infrastructure are only measured in a meaningful way in the 2007 census. Therefore, we use them across all three waves. Similarly, given that the information for access to electricity is only available in the 2000 census we examine the impact of its interaction with rainfall across all three waves.

We aggregate the *barangay*-level data at the municipality level.[13] The primary reason for this rests with the fact that *barangays* are relatively small in terms of population size and area. The lack of accessibility to a certain facility or type of infrastructure within any given *barangay* does imply that this facility is not available in the neighboring *barangay*. [14]

Results

The main results of our analysis are in table 2. For rainfall, the omitted category is to have rainfall within one standard deviation of the municipality long-term average. We find that facing a negative rainfall shock, i.e. rainfall below 1 standard deviation of the long-run average in the municipality, decreases consumption by about 4%. In contrast, the coefficient on positive shocks is at about 2% at most and often not significant. However, because of the large standard errors, the difference between the two coefficients is not significant. [15]

Table 2

The results are similar with and without municipality fixed effects. They are also unchanged when we control for a few basic household characteristics, except that the coefficient on the positive shock becomes significant.

Table 3

In Table 3, we examine whether agricultural households are affected more by shocks. Whether this is true depends on the magnitude of the two channels, other than income, through which rainfall shocks affect consumption: prices, mostly of agricultural goods, and general equilibrium effects. While we only conduct reduced form estimates, the results in table 3 point to the fact that rainfall shocks have a widespread impact in rural areas: they affect agricultural and non agricultural households alike. By contrast to agricultural

[13] Much to our surprise, the FIES is actually a panel of *barangays*. We find this surprising because the sampling design, while having some enumeration areas with probability of selection very close to 1, should not lead, if random, to a dataset where almost all *barangays* are interviewed in the 3 waves of the FIES.
[14] On average, dividing the Philippines population by the number of municipalities and of *barangays* in the country, we find that a *barangay* comprises a population of 2,217 while a municipality comprises 57,301 individuals. Hence, controlling for variables at the municipality level may be more meaningful than simply controlling for them at the *barangay*-level. Explanation of the variables and how they are aggregated at the municipality level is contained in appendix B.
[15] In Appendix A we carry out a variety of robustness checks using alternative measures of the rainfall shock.

households, households receiving remittances could be protected from negative shocks. Contrary to Yang and Choi (2007), we do not find this result, as can be seen in the last 2 columns of table 3.

Table 4

In table 4, we examine whether the impact of shocks differs for the lower 30% of the distribution.[16] We could expect the impact of shocks to be stronger for the poor if they have a more limited ability to protect from shocks, for instance through using savings. Actually, the coefficient on negative shocks is identical across the two parts of the distribution. For both groups, the adverse impact on consumption is driven by food expenditure, for which the coefficients on negative and positive shocks are significantly different. By contrast, shocks, whether negative or positive, do not have an impact on non-food expenditure. This is rather contrary to what we would expect. We would expect and certainly hope that households are able to protect basic needs, of which food is the main component. One potential explanation for this result is that a negative rainfall shocks may increase the price of food, in particular rice, and there may be some substitution away from it.

Hence, it is for food consumption that negative and positive shocks have an asymmetrical impact, with negative shocks decreasing food consumption while positive shocks have no impact. Climate change is then likely to adversely affect food consumption.

Hence, these results point to the fact that climate change is likely to have an impact on household welfare; in particular, through affecting basic needs such as food. While negative rainfall shocks decrease household food consumption by about 4%, positive shocks have no impact or a very limited impact, which is at most of 1%. An increase in shocks, positive and negative, is then likely to hurt household food consumption. Even if the mean of rainfall increases, which may happen in some areas, this may not benefit households if negative shocks also occur more often. When we examine total expenditure, while negative shocks seem to have a larger impact than positive shocks, they are not significantly different from each other and it is then unclear whether climate change would have an impact on total household expenditure.

While it hints toward potential impact of climate change, the reason behind the larger impact of negative shocks may be borrowing constraints.,Assuming positive shocks are temporary and thus not affecting permanent income, they may be saved, consequently, leaving consumption unchanged. On the other hand, negative shocks decrease consumption because households are unable to borrow to maintain food consumption.

[16] The "poor" in this case are defined as the bottom 30% of the distribution of per capita expenditure in each year. We do this to make sure that the definition is not driven by changes in the distribution of consumption from one survey to the next. By taking 30% as the threshold we are then close to the poverty rate of the Philippines, also including those who are just above. In the Philippines, the poverty rate was 33% in 2000, 24.9% in 2003, 26.4% in 2006 and 26.5% in 2009.

We now turn to the distribution of the impact of rainfall shocks across the regions of the Philippines, as well as across differences in access to infrastructure and diversification of activities in the municipalities of the FIES.

Table 5

Table 5 displays the impact of rainfall shocks across regions. To help understand the results and the geographic distribution of the impact, column (1) presents the island where the regions are. Column (2) presents the regions. We have grouped some regions that were close to each other, in particular when the occurrence of one type of shock was very low and, as a consequence, likely not to be meaningful.[17] The average impact of each type shock in each region is presented in column (4). These are not marginal effects compared to an omitted region. The -0.095 coefficient on the negative shock in Ilocos means that in this region, compared to rainfall within one-standard deviation of the long-run average, a negative shock decreases household consumption by 9.5%. The regions mainly affected by negative rainfall shocks are Ilocos, which is in the North-Western part of Luzon as well as Western Visayas Islands. In Bicol, while it is estimated with less precision, the negative rainfall shock also has a large negative coefficient.

Comparing the magnitude of negative rainfall shocks to that of positive shocks, we see that Western Visayas is the region most at risk with respect to climate change, with an impact of negative shocks of 9% versus no impact of positive shocks. By contrast, and even though positive shocks are not estimated with precision, in Central Visayas and Eastern Visayas, the magnitudes of the coefficients on positive and negative shocks are close and there is no asymmetry between them. This is also true in Ilocos. In the case of Mimaropa, it is hard to predict anything because it did not experience a negative shock during the time of the surveys we use but it is region where an increase in rainfall is predicted due to climate change and it seems to benefit from positive shocks on rainfall.[18]

Table 6

The results for infrastructure variables and their interactions with the rainfall shocks are in table 6. Due to high correlation between distance to the highway and distance to a ground line, we include them separately. We first examine the interaction of the distance to the highway with the rainfall shock, in columns (1) to (3) and then examine distance to a fixed line phone in columns (4) and (5) and finally include the measures together with distance to a cell phone signal as well as access to electricity in the municipality. The summary of table 6 is that the impact of negative rainfall shocks increases with an increase in the

[17] When a type of shock was affecting fewer than 100 households in a given region, we grouped the region with another one on the same island.

[18] We need to point out the negative coefficient on positive shocks in Central Luzon is misleading and due to a small number of households benefitting from positive shocks over the period in that region: only 140. We have not merged in our estimates Central Luzon with another region because it is a key region for rice production and our criterion to merge region was to have fewer than 100 households affected by a given outcome. However, this result is likely driven by the small number of observations.

distance of *barangays* in the municipality from the highway and from a fixed line phone.[19] The impact of the negative rainfall shock is more than twice as high for the 9th decile of the distance from the highway, as for the average distance from the highway – -10% versus -4.5%. The impact of the negative shock is nil for households which are close to a highway; i.e. with total distance below the 17th percentile of the distribution of the distance to/from the highway. Similarly, for distance to fixed line phone, the impact of negative shocks is 0 for the households in the first quartile of the distance to a fixed line phone. For those households in the 9th decile, the impact of the negative rainfall shock is double when compared to those at the average. By contrast, distance to a cell phone does not have an impact. Similarly, access to electricity does not seem to change the impact of a negative shock. In this latter case, with the variable dating to 2000, it may not capture accurately the situation of households in 2006 or 2009.

Table 7

In table 7, we turn to whether municipalities which have access to a market or have diversified activities, as measured by a higher number of non-agricultural firms, witness a smaller impact of negative rainfall shocks. First, we examine the interaction of distance to market with the negative rainfall shock. Access to markets allows increasing distribution of what is produced in the municipality and, in case of local shocks, it should help decrease prices after a drought. Indeed we find that the impact of the shock increases when distance to market increases.

For diversification in the municipality, in columns (3) to (6), we follow what we did for infrastructure and include each type of establishment separately. This is because the correlation between the numbers of establishments is higher than 75%. We do not find any smoothing impact of activities outside of agriculture. In column (3), an increase in the number of commercial establishments in the municipality does not help decrease the impact of negative shocks. While commercial establishments can be measure of the ability to distribute products and decrease prices, commercial activities, like other services in column (5), which do not have a smoothing impact either, can also be affected by general equilibrium effects and this seems to be the case here. In column (4) we examine the interaction of the number of manufacturing establishments with the shock. This is a measure of diversification away from agriculture and manufacturing activities should not be affected by rainfall. Surprisingly we do not find that having a higher number of manufacturing establishments decreases the impact of shocks. Lastly, in column (6) we examine whether the presence of banks or other financial institutions helps smooth the impact of adverse rainfall shocks. Such presence should decrease household borrowing constraints and improve their capacity to save and conduct risk management *ex-ante*. Also somewhat surprisingly: we do not find an impact of these establishments.

[19] We have three different measures of the distance to the highway. In column (1), we include the distance in kilometers which is only available in 2003. In column (2), we include the proportion of barangays in the municipality that are within 5 kilometers. In column (3) we simply sum the distance of all the barangays in the municipality. For distance to fixed line phone and distance to cell phone, we have the equivalent measures as those in columns (2) and (3) for the highway.

In summary, improving communication and transportation seem to be the means to help decrease the impact of adverse rainfall shocks.

Concluding Remarks and Policy Considerations

Carefully matching three rounds of a large regionally representative household survey with rainfall data from 48 weather stations across the Philippines, we have examined the impact of rainfall shocks on household consumption. We find results that point to an adverse impact of climate change. Negative rainfall shocks decrease total expenditure as well as food expenditure by about 4%. In contrast, positive shocks do not lead to limited improvements in total expenditure and no improvement in food expenditure. Hence, in a scenario where the average level of rainfall is unchanged but where there is an increase in the occurrence of periods with high rainfall as well as periods with low rainfall, then household consumption will be hurt. Indeed, while households will be affected by periods of drought, they will not gain from periods with high rainfall.

The finding that the shock affects mainly food expenditure is contrary to what we were expecting. One possible explanation for this result may be that rainfall shocks affect food prices. This is in line with the fact that we do not find that agricultural households are affected harder by negative rainfall shocks.

One important finding from our analysis is that access to communication, highways, and markets decreases considerably the impacts of rainfall shocks. This suggests that many of the policies that can be effective at reducing the impacts of climate change on poverty in the Philippines are not different from the strategies of sound development agendas aimed at reducing poverty and promoting economic growth. The most important elements of such policies include: i) smoothing the price impacts of regional or country-specific climate shocks through international trade; ii) investing in human capital to increase employment opportunities of the poor, accompanied by policies and incentives that facilitate the migration of the poor to the areas with better economic opportunities; iii) providing credit and developing insurance markets; iv) investing in transportation and communication infrastructure; v) investing in irrigation and/or improved water management to deal with extreme precipitation events; vi) investing in adaptive agricultural research and in information and extension services; vii) improving governance of common-pool natural resources; and creating well targeted and scalable safety nets systems.

Interventions that help improve communication and access to markets should be a critical component of country-level adaptation strategies. In particular, safety net systems that are counter-cyclical, such as conditional and unconditional cash transfers, workfare programs (e.g., food or cash-for work), and social funds (community-level programs in infrastructure, social services, training, etc.) can have immediate pay-offs since they enable countries to deal with economic crises and other shocks that may not be related to climate change and climatic variability.

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Figure 1 - Impact of rainfall shocks on consumption

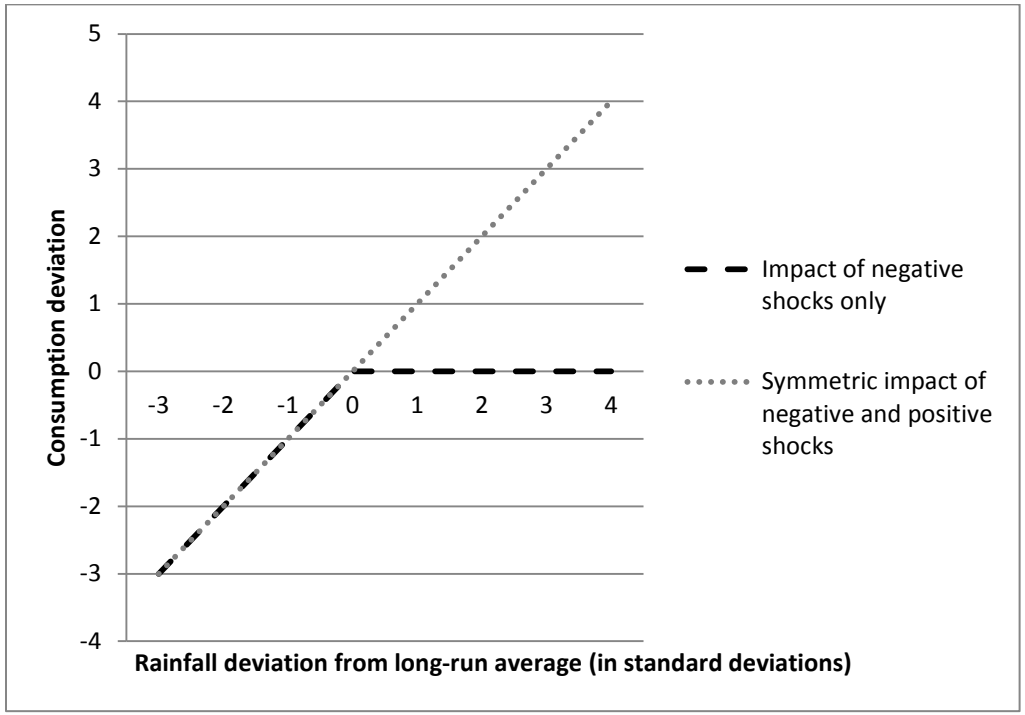

Figure 2 - Distribution of rainfall stations

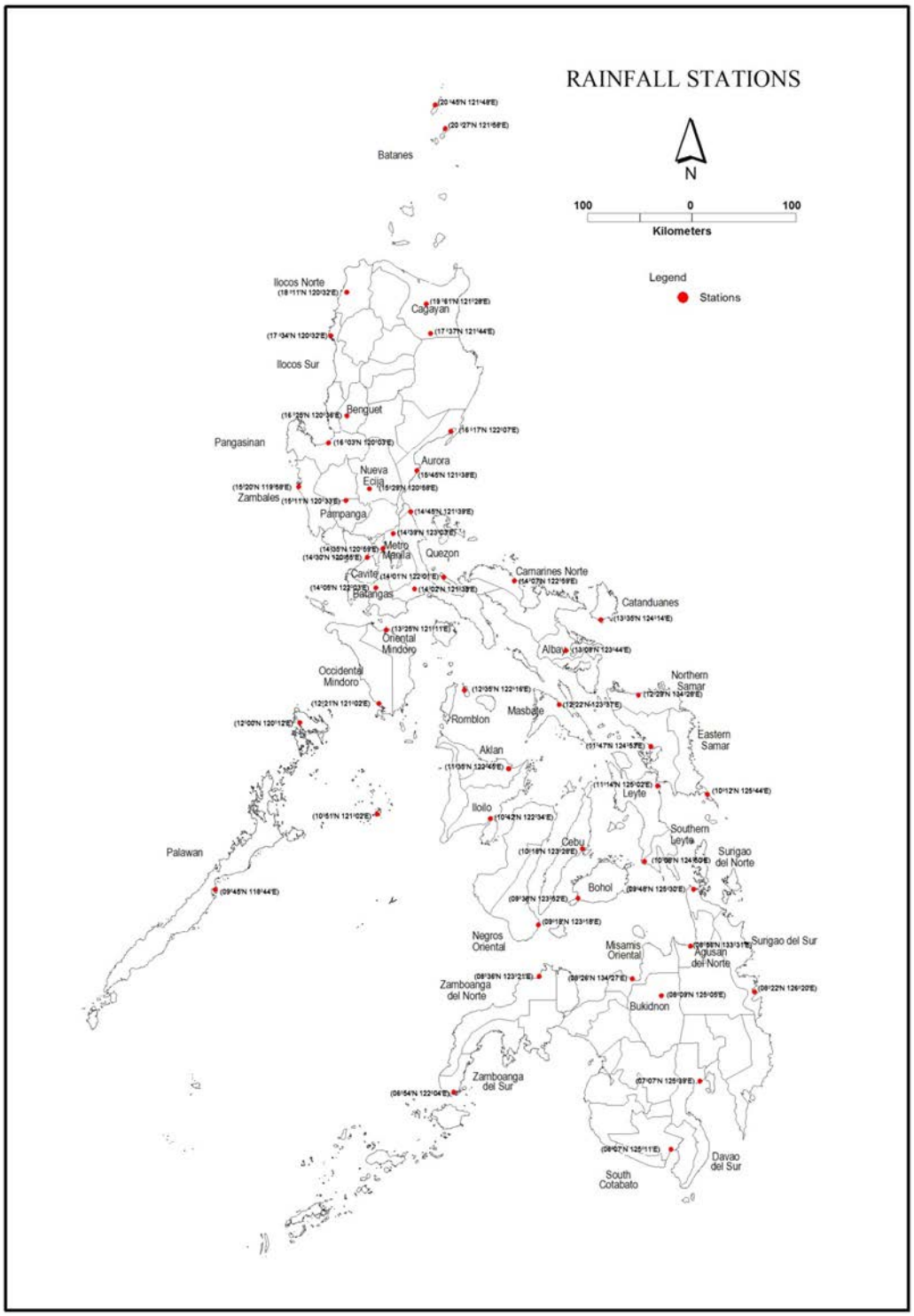

Figure 3 - Average Annual Rainfall (in mm)

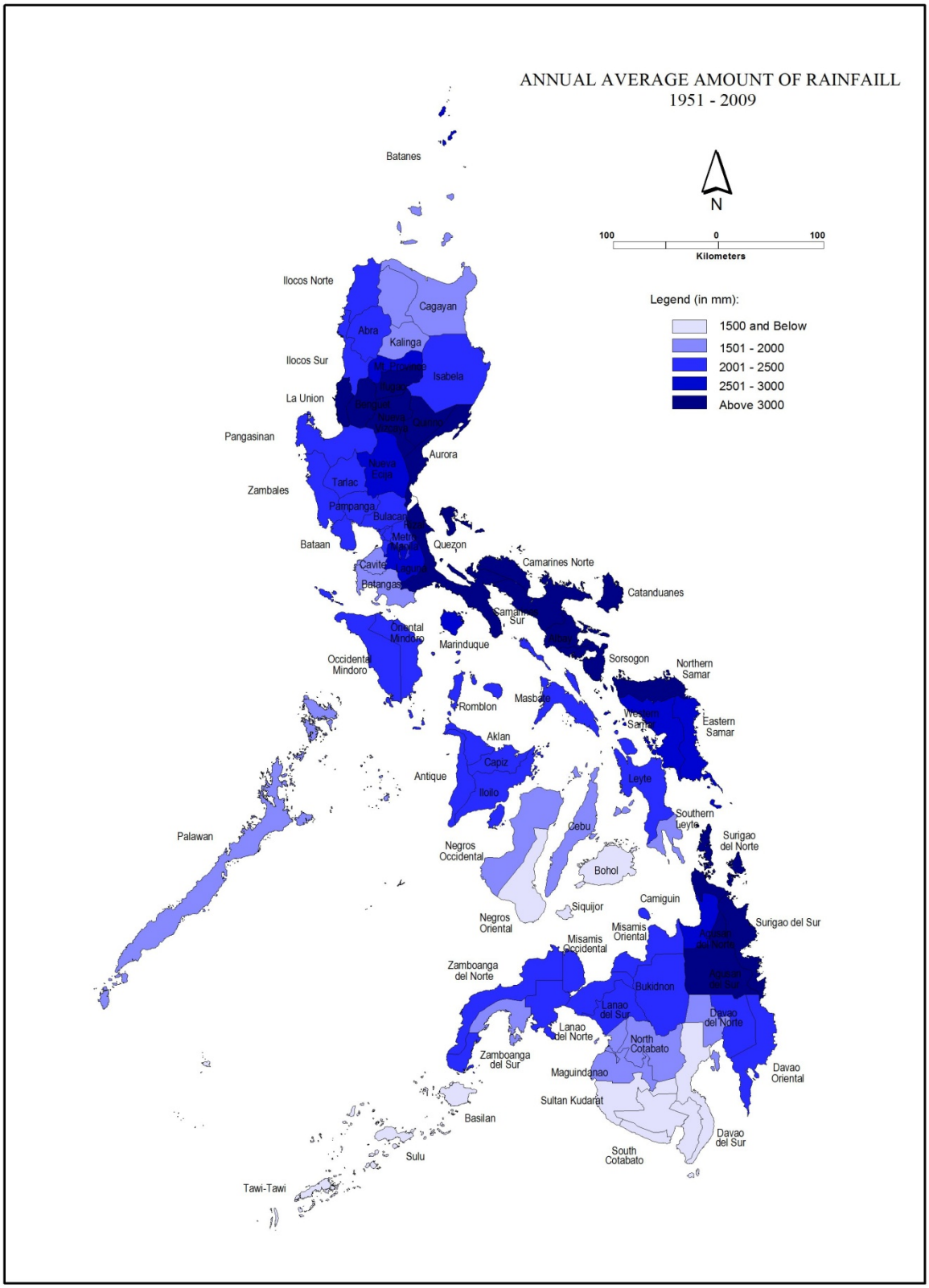

Figure 4 Distribution of rainfall deviation in the years before the FIES survey

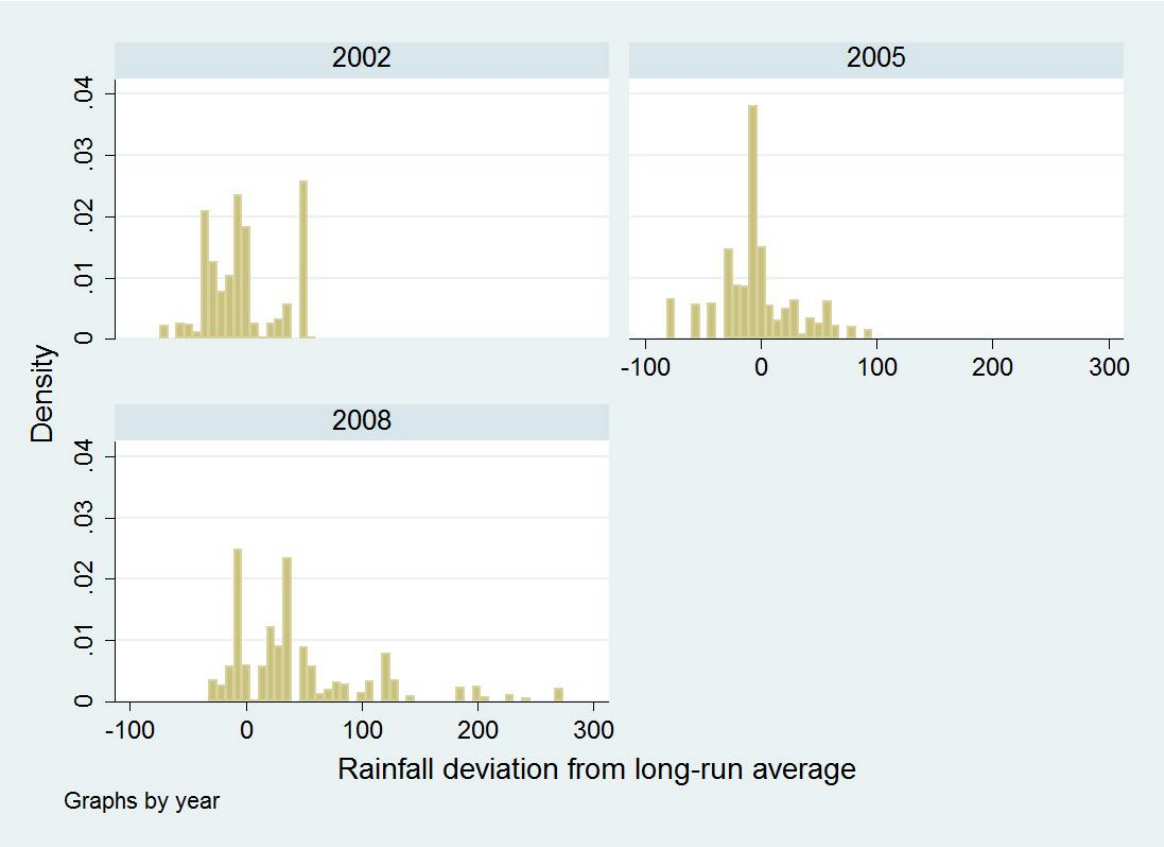

Table 1 – Frequency of the rainfall shocks depending on the threshold chosen to define the shock

Shock definition threshold	Year		
	2002	2005	2008
Half a standard deviation			
R > mean + 0.5 standard deviation	0.22	0.18	0.61
R< mean - 0.5 standard deviation	0.34	0.29	0.02
mean - 0.5 standard deviation < R < mean + 0.5 standard deviation	0.44	0.53	0.37
One standard deviation			
R > mean + 1 standard deviation	0	0.09	0.5
R< mean - 1 standard deviation	0.16	0.09	0
mean - 1 standard deviation < R < mean + 1 standard deviation	0.84	0.82	0.5
Two standard deviations			
R > mean + 2 standard deviations	0	0	0.28
R< mean - 2 standard deviations	0	0	0
mean - 2 standard deviations < R < mean + 2 standard deviations	1	1	0.72

Table 2 - Impact of rainfall shocks on total per capita expenditure

	(1)	(2)	(3)
Positive rainfall shock	0.004	0.016	0.020*
	(0.012)	(0.012)	(0.011)
Negative rainfall shock	-0.031**	-0.043***	-0.040***
	(0.014)	(0.014)	(0.014)
Female HH head			0.009
			(0.006)
HH head Age			0.007***
			(0.000)
Household Size			-0.110***
			(0.001)
HH Head Education (ref: no education):			
• Elementary Undergraduate			0.145***
			(0.013)
• Elementary Graduate			0.277***
			(0.015)
• High School Undergraduate			0.369***
			(0.017)
• High School Graduate			0.491***
			(0.017)
• College Undergraduate			0.749***
			(0.020)
• College Graduate			1.203***
			(0.026)
Constant	5.505***	5.531***	5.382***
	(0.012)	(0.005)	(0.020)
Observations	65,355	65,355	65,355
R-squared		0.003	0.397
Number of mun_id_2011	915	915	915
Municipality FE	NO	YES	YES
Municipality RE	YES	NO	NO

The estimates control for year dummies. Standard errors are clustered at the municipality level.
*** p<0.01, ** p<0.05, * p<0.1

Table 3 - Impact of rainfall shocks for agricultural households

	(1)	(2)	(3)	(4)	(5)	(6)
Definition of "in agriculture"		Growing of crops	(2) + farming of animals and ag. services	(3) + hunting and forestry		
Positive rainfall shock	0.014	0.018	0.018	0.018	0.016	0.017
	(0.011)	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)
Negative rainfall shock	-0.049***	-0.048***	-0.054***	-0.056***	-0.044***	-0.035*
	(0.015)	(0.017)	(0.017)	(0.017)	(0.014)	(0.018)
Negative rainfall shock*HH Hd in agriculture	0.022	0.010	0.021	0.026		
	(0.021)	(0.023)	(0.022)	(0.021)		
HH Hd in agriculture	-0.389***	-0.212***	-0.233***	-0.244***		
	(0.010)	(0.014)	(0.013)	(0.012)		
Negative rainfall shock*Log of Remittances					0.003	0.002
					(0.002)	(0.002)
Log of remittances					0.044***	0.044***
					(0.001)	(0.001)
Negative rainfall shock*Log of domestic transfers						-0.002
						(0.002)
Domestic transfers						-0.007***
						(0.001)
Constant	5.709***	5.634***	5.653***	5.660***	5.466***	5.491***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)
Observations	65,355	65,355	65,355	65,355	65,355	65,355
R-squared	0.425	0.402	0.403	0.404	0.443	0.446
Municipality FE	YES	YES	YES	YES	YES	YES

The estimates control for year dummies. Standard errors are clustered at the municipality level.
*** p<0.01, ** p<0.05, * p<0.1

Table 4 - Separating the impact of shocks across consumption

	(1)	(2)	(3)	(4)	(5)	(6)
	Consumption in lower 30%			Consumption in top 70%		
	Total	Food	Non food	Total	Food	Non food
Positive rainfall shock	0.009	0.006	0.015	0.011	0.011	0.013
	(0.008)	(0.010)	(0.012)	(0.010)	(0.009)	(0.015)
Negative rainfall shock	-0.027***	-0.044***	0.003	-0.023**	-0.038***	-0.002
	(0.010)	(0.014)	(0.017)	(0.011)	(0.012)	(0.015)
Constant	4.969***	4.504***	3.953***	5.935***	5.217***	5.193***
	(0.004)	(0.004)	(0.006)	(0.004)	(0.005)	(0.006)
Observations	27,655	27,655	27,655	37,700	37,700	37,700
R-squared	0.017	0.024	0.005	0.003	0.008	0.003
Municipality FE	YES	YES	YES	YES	YES	YES

The estimates control for year dummies. Standard errors are clustered at the municipality level. There are 913 municipalities.
*** p<0.01, ** p<0.05, * p<0.1

Table 5 - Impact of rainfall shocks across regions

Island	Region	Type of shock	(1)
Luzon Island	Ilocos	Positive rainfall shock	0.034
			(0.044)
		Negative rainfall shock	-0.095***
			(0.035)
	Cagayan Valley	Positive rainfall shock	0.030
			(0.026)
		Negative rainfall shock	.019
			(.054)
	Central Luzon (rice granary)	Positive rainfall shock	-0.130*
			(0.066)
		Negative rainfall shock	-0.036
			(0.036)
	Bicol	Positive rainfall shock	0.053**
			(0.025)
		Negative rainfall shock	-0.080
			(0.051)
	CAR	Positive rainfall shock	-0.036
			(0.054)
		Negative rainfall shock	0.058
			(0.083)
	Calabarzon (predicted increase in rainfall)	Positive rainfall shock	0.017
			(0.044)
		Negative rainfall shock	0.002
			(0.030)
Mindoro, Palawan	Mimaropa (predicted increase in rainfall) no negative shock	Positive rainfall shock	0.036
			(0.004)
Visayan Islands	Western Visayas	Positive rainfall shock	0.001
			(0.023)
		Negative rainfall shock	-0.091***
			(0.024)
	Central Visayas and Eastern Visayas	Positive rainfall shock	0.042
			(0.023)
		Negative rainfall shock	-0.055**
			(0.045)
Mindanao	Western, Northern, Southern and Central Mindanao and ARMM and Caraga	Negative rainfall shock	-0.004
			(0.016)
		Positive rainfall shock	-0.007
			(0.041)
		Constant	5.530***
			(0.010)
		R-squared	0.003
		Municipality FE	YES

Total number of observations is 65,355 households. The estimates also control for year dummies. Standard errors are clustered at the municipality level. There are 915 municipalities. ***
p<0.01, ** p<0.05, * p<0.1

Table 6 – Which infrastructure help decrease the impact of negative rainfall shocks?

VARIABLES	(1) 2003 var Dist in km	(2) 2006 var % of barangays within less than 5km	(3) 2006 var total distance of barangays	(4) 2006 var % of barangays within less than 5km	(5) 2006 var total distance of barangays	(6) 2006 var total distance of barangays	(7) 2006 var % of barangays within less than 5km
Positive rainfall shock	0.0181	0.0158	0.0170	0.0172	0.0166	0.0179	0.0182
	(0.0120)	(0.0120)	(0.0120)	(0.0121)	(0.0120)	(0.0120)	(0.0121)
Negative rainfall shock	-0.0332*	-0.0081	-0.0088	-0.0324	0.0061	0.0114	-0.0473
	(0.0187)	(0.0475)	(0.0227)	(0.0321)	(0.0280)	(0.0711)	(0.2120)
Negative rainfall shock*Distance to highway	-0.0000	-0.0580	-0.0003**			-0.0001	-0.0715
	(0.0000)	(0.0771)	(0.0001)			(0.0002)	(0.0762)
Negative rainfall shock*Distance to fixed line phone				-0.0193	-0.0009**	-0.0006	-0.0308
				(0.0588)	(0.0004)	(0.0007)	(0.0704)
Negative rainfall shock*Distance to cell phone signal						-0.0005	0.0114
						(0.0010)	(0.2254)
Negative rainfall shock*Electricity						-0.0042	0.0636
						(0.0715)	(0.0781)
Constant	5.5324***	5.5319***	5.5329***	5.5347***	5.5331***	5.5333***	5.5351***
	(0.0052)	(0.0052)	(0.0052)	(0.0053)	(0.0052)	(0.0053)	(0.0053)
Observations	64,361	64,664	64,664	63,965	64,664	64,522	63,823
R-squared	0.0030	0.0029	0.0030	0.0029	0.0030	0.0031	0.0030
Number of mun_id_2011	909	908	908	896	908	904	892
Municipality FE	YES	YES	YES	YES	YES	YES	YES

The estimates also control for year dummies. Standard errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1

Table 7 - Diversification of activities in the municipality and impact of negative rainfall shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Total distance of barangays	% of barangays within less than 5km	Total number	Total number	Total number	Total number	Total number
dev_mean_all_a_pos_m1sd	0.017	0.016	0.016	0.016	0.016	0.016	0.016
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
dev_mean_all_a_neg_m1sd==1	0.008	-0.069	-0.046***	-0.034*	-0.040**	-0.048***	-0.037**
	(0.026)	(0.046)	(0.016)	(0.018)	(0.018)	(0.016)	(0.016)
Negative rainfall shock * Distance to market	-0.001***	0.045					
	(0.000)	(0.075)					
Negative rainfall shock * N Commercial establishments			0.000				
			(0.000)				
Negative rainfall shock * N Manufacturing establishments				-0.000			
				(0.000)			
Negative rainfall shock * N Services					-0.000		
					(0.000)		
Negative rainfall shock * N hotels						0.000	
						(0.000)	
Negative rainfall shock * N Banks							-0.000
							(0.000)
Constant	5.532***	5.532***	5.532***	5.532***	5.532***	5.532***	5.532***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	64,664	64,601	64,664	64,664	64,664	64,664	64,664
R-squared	0.003	0.003	0.003	0.003	0.003	0.003	0.003
Municipality FE	YES	YES	YES	YES	YES	YES	YES

The estimates also control for year dummies. Standard errors are clustered at the municipality level.
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX A – ROBUSTNESS CHECKS

In this Appendix we carry out a variety of robustness checks by presenting the estimates obtained using alternative measures of the rainfall shock based only those municipalities for which rainfall data are never missing. In columns (1) and (2) of table A.1, we include the deviation of log rainfall from the long-term mean, whereas in columns (3) and (4) we distinguish between positive and negative deviations. While the coefficients are not estimated with precision, we can see that the coefficient on the negative deviation is twice as high as the coefficient on the positive deviation. The last two columns of table A.1, present results using as a measure of shock a binary variable identifying whether rainfall was more than half a standard deviation above or below the long-run average.

In table A.2, we return to the main measures of the shock we use, the dummies for large shocks, but we restrict the sample to observations for which the measure of rainfall shock may be considered as more accurate. In column (1), we only keep years and municipalities for which there is no month with missing data in the three years before the FIES rounds. This drops the sample size considerably but the results are qualitatively the same for negative shocks. In this case, the impact of positive and negative shocks seems symmetric, which would say that there would be no impact on average of climate change. However, when we increase the number of observations by including observations with one month of missing data (column (2)) or two months of missing data (column (3)), the results are the same as in table 2, with the impact of negative shocks being twice as high as that of positive shocks. This is also true when we restrict the sample to municipalities which have a rainfall station on the same island, as can be seen in column (5). Columns (6) and (7) restrict the sample in (5) to observations with either no month with missing data (column (6)) or no more than one month with missing data (column (7)) and the results are the same as in columns (1)-(2).

Table A.1- Impact of alternative measures of rainfall on consumption

	(1)	(2)	(3)	(4)	(5)	(6)
Deviation of log rainfall	0.039	0.041*				
	(0.025)	(0.023)				
Positive deviation of log rainfall			0.029	0.032		
			(0.030)	(0.028)		
Negative deviation of log rainfall			0.058	0.060		
			(0.052)	(0.048)		
Rainfall more than half a st. dev above average					0.008	0.009
					(0.010)	(0.009)
Rainfall more than half a st. dev below average					-0.013	-0.017*
					(0.011)	(0.010)
Female HH head		0.009		0.009		0.009
		(0.006)		(0.006)		(0.006)
HH head Age		0.007***		0.007***		0.007***
		(0.000)		(0.000)		(0.000)
Household size		-0.110***		-0.110***		-0.110***
		(0.001)		(0.001)		(0.001)
HH Head Education (ref: no education):		0.145***		0.145***		0.145***
• Elementary Undergraduate		(0.013)		(0.013)		(0.013)
		0.277***		0.277***		0.277***
• Elementary Graduate		(0.015)		(0.015)		(0.015)
		0.369***		0.369***		0.369***
• High School Undergraduate		(0.017)		(0.017)		(0.017)
		0.491***		0.491***		0.491***
• High School Graduate		(0.017)		(0.017)		(0.017)
		0.749***		0.749***		0.749***
• College Undergraduate		(0.020)		(0.020)		(0.020)
		1.203***		1.203***		1.204***
• College Graduate		(0.026)		(0.026)		(0.026)
Constant	5.527***	5.379***	5.530***	5.381***	-0.004	-0.030***
	(0.005)	(0.020)	(0.007)	(0.021)	(0.008)	(0.007)
Observations	65,355	65,355	65,355	65,355	65,355	65,355
R-squared	0.003	0.397	0.003	0.397	0.003	0.397

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.2 - Robustness checks on the impact of rainfall shocks on consumption

VARIABLES	(1) No missing rainfall data	(2) Maximum 1 month with missing rainfall data	(3) Maximum 2 months with missing rainfall data	(5) Only municipalities with rainfall station on same island	(6) Only municipalities with rainfall station on same island and no missing rainfall data	(7) Only municipalities with rainfall station on same island and maximum 1 month with missing rainfall data
Positive rainfall shock	0.025*	0.013	0.017	0.019	0.027*	0.019
	(0.014)	(0.013)	(0.013)	(0.012)	(0.014)	(0.013)
Negative rainfall shock	-0.027	-0.047***	-0.046***	-0.041***	-0.028	-0.044***
	(0.017)	(0.014)	(0.014)	(0.014)	(0.017)	(0.015)
Constant	5.594***	5.573***	5.563***	5.540***	5.598***	5.584***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
Observations	38,689	50,107	53,733	61,006	38,195	46,827
R-squared	0.003	0.003	0.003	0.003	0.003	0.003
N municipalities	525	691	743	847	515	640
Municipality FE	YES	YES	YES	YES	YES	YES

The estimates include controls for year dummies. Standard errors are clustered at the municipality level.
The number of months with missing rainfall data is calculated over the 36 months of 2002, 2005 and 2008, when the rainfall shock is measured.
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX B – DATA CONSTRUCTION

Construction of the consumption aggregate

The consumption aggregate comparable across provinces and over the three FIES periods (2003, 2006 and 2009) is constructed by dividing nominal expenditures with the ratio of the province specific poverty line with the poverty line in Manila in the year 2009. The latter ratio adjusts for costs of living differences across provinces and over time and expresses nominal consumption expenditures in any province and in different years in terms of 2009 prices in Manila. Specifically, the per capita expenditures of household h in province p in year t are adjusted as follows:

$$AdjPCE(h,p,t) = \frac{PCE(h,p,t)}{PL(p,t) \big/ PL(Manila, t = 2009)}$$

A similar adjustment is made when we examine food expenditures. Adjusted non-food expenditures are derived from the difference between adjusted PCE and adjusted Food expenditures per capita.

Rainfall

The rainfall data is drawn from 48 rainfall stations across the Philippines. We dropped 5 stations. In one case (station 4 on Basco Batanes), it is because it is not the closest station to any municipality centroid in FIES. In the four other cases, the stations were dropped because the latest year with data available was before 2002, *i.e.* before the first year of data for our estimates. We decided to drop these stations because imputing data to calculate a long-run average or calculating a long-run average dropping some years is fine since we calculate the average over 25 years and if there is some artificial variation brought about by imputation, it is likely to be partially wiped out in the 25-year average. By contrast, for the years of the shock, it is by definition only one year that is used and we did not want to create variation artificially by imputing values in the years when we need to calculate rainfall shocks.

In these 4 cases, we have checked whether rainfall data in neighboring stations, used to replace these stations dropped, was close to the rainfall data in the stations dropped (in the years when data was available in both).

Details of stations dropped:

Station **1**: data is missing from 1993 onward.

- Replaced with the second closest station to each municipality. A problem however is that, among the stations that are very close to station 1, on station – station 37 – has rainfall that is about 25% higher. The value of rainfall in stations 2 and 12, the next 2 closest stations, are much closer to the value of rainfall in station 1 but we decided not to make an arbitrary

decision and an exception to the rule of replacing with the second closest station.

- Station **32**: data is missing starting from 1987. Differences in rainfall with neighboring stations are large. This might be due to the fact that the station is in Samar, a relatively small island and the weather stations are close to the coast.
- Station **33**: latest year with non-missing data is 1994. Rainfall in station 33 is at the median of surrounding stations for rainfall in 51-94. And in particular very close to the values of station 6, which is the closest station.
- Stations **34**: data from 52 to 94 only. The closest station has data starting from 1977. Over the 24 years with data for both, there are only 3 years where the difference between the 2 is above 20%, but 14 years where the difference is above 10%.

We have obtained data going back to 1949, for some rainfall stations. However, we build our long-run average using only 24 years, from 1977 to 2001. This is because for some rainfall stations, data was missing before 1977 and we did not want to create artificial differences between stations depending on missing data. For stations for which older data was available, we compared the mean starting in 1977 to the mean starting earlier and they were quite close. We made one exception to the rule of having 1977 as the first year to calculate the long run average, for one station had its earliest year in 1981.

Among stations for which earliest year is before 1977 and latest year is after 2009, there were 3 stations for which data was missing at least once for a whole year (station 2 had data missing for all of 1981, station 23 had data missing for all of 1991 and station 26 had data missing for 1979-1983). We calculated the long-term mean dropping the missing years. For station 26, we compared the means and totals of rainfall for stations close to station 26, over 1977-2000, with and without including 1979-1983 and they are very similar.

In other cases, when data is missing, we have imputed values following two different rules and compared estimates with the two different methods as well as without imputing values and there was not much difference.

Specification of the two different methods of imputation:

- One station (station 48) has its earliest year in 1986 and has data missing for all of 2008:
    - Method E: we kept the station and imputed the value for 2008 only
    - Method A: we dropped the station
- One station has data in 2008 missing for the whole year:
    - Method E: we replaced the 2008 value with value from closest station
    - Method A: we dropped the station. Because there are lots of year-on-year variation within close stations. Even the rank in terms of what is

the station with most rain changes. Station 27 seems in the middle but in 2007 and 2009, more rainfall in station 27 than in station 48

- When a few months are missing in a given year (the case in point is 2008, when 14 stations with at least 1 month missing
    - Method E: replace the missing month with data from the closest station
    - Method A: no replacement

Infrastructure

Census data used and variables therein

We use census data module 5 for 2000 and 2007.

We merge the 2000 census with the 2003 round of the FIES and the 2007 census with the 2006 and 2009 rounds. However, the 2000 and 2007 rounds only have a few infrastructure variables of interest to us that are exactly the same and coded the same way. Hence, in many instances, we use only round, and consider that the value is constant across the 2000 and 2007 census.

More precisely, the variable market is the only variable that is recorded in the same way in both 2000 and 2007. All other variables we use, with one exception, are only defined in 2007. The exception is access to electricity in the *barangay*, which is only recorded in 2000.

For instance, the variables on the presence of different types of establishments are recorded in 2000 and 2007. However, in 2000, only the establishments in the barangay are recorded, while in 2007 the values recorded are also those of establishments within 2km of the barangay. In addition, in 2000, the variables are truncated at 10 and as a result, they contain much less information than the 2007 variables which record the exact number of establishments present, even if it higher than 10.

Aggregation

We aggregate the *barangay*-level data at the municipality level. We explain below the different variables available and the types of aggregation depending on the variable.

For fixed phone line and cell phone signal, distance from the municipality is recorded as 1 when the facility is within 2km, 2 when the facility is beyond 2 km but within 5 km and 3 when the facility is beyond 5km.

For distance to highway, the coding is similar but only when the *barangay* "has access" – *i.e.* before recording distance, there is a filter variable about access and the

question on distance is skipped in case the barangay does not have access to the highway. In the case of the highway, the distance has only been recorded when the barangay "has access", we have coded the distance variable as "10" for barangays that do not have access.

For these 3 variables for which distance has been recorded as a categorical variable, we aggregate the distance at the municipality level in 2 ways:

- Proportion of barangays in the municipality that have a facility within less than 5 kilometers

- Total of the barangay distances in the municipality. Doing this does not give an accurate measure since, depending on where a given facility is, say for instance a highway, the same total of distances may correspond to 2 very different situations in terms of distance. However, the information is richer than the first measure in the case of the highway. In this case, the first measure does not separate barangays which do not have access to a highway from barangays that have access but that are more than 5km away.

For market (resp. electricity), the *barangay* variable is a dummy equal to 1 if the *barangay* has a regular market (resp. access to electricity). Hence, the aggregate variable is the proportion of barangays in the municipality with the value of the dummy equal to 1.

For other variables about the number of establishments, the aggregate variable is the total of the variable for each barangay. We simply capture by the total number of establishments in the municipality.

If the value is missing in a *barangay*, it counts as 0. When we restrict estimates to municipalities where there is no *barangay* with missing data, the results are unchanged.