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Poverty and natural disasters: A meta-analysis

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POVERTY AND NATURAL DISASTERS: A META-ANALYSIS

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ABSTRACT:

We conduct a meta-regression analysis of the existing literature on the impacts of disasters on households, focusing on the poor and on poverty measures. We find much heterogeneity in these impacts, but several general patterns, often observed in individual case-studies, emerge. Incomes are clearly impacted adversely, with the impact observed specifically in per-capita measures (so it is not due to the mortality caused by the observed disaster). Consumption is also reduced, but to a lesser extent than incomes. Importantly, poor households appear to smooth their food consumption by reducing the consumption of non-food items; the most significant items in this category are spending on housing, health, and education. This suggests potentially long-term adverse consequences as consumption of these services is often better viewed as long-term investment. We do not find consistent patterns in long-term impacts; it appears the limits of the meta-regression methodology prevent us from observing patterns in the relatively few heterogeneous research projects that examine these long-term effects. The importance of addressing risk within the context of sustainable development and poverty alleviation is clear. The impact of disasters on the poor may be increasingly worrying considering the climate variations we anticipate.

Key words: disaster, natural, poverty.

JEL codes: I3, Q54, Q56

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1. Introduction

Natural disasters - earthquakes, typhoons, hurricanes, floods, cold and heat waves, droughts and volcanic eruptions - are a constant presence in all our lives, but especially so for the poor. Disasters are especially prevalent in the most populous region of the world (Asia) and most catastrophic in the destruction they wreak in the poorest countries (e.g., Haiti in 2010). Disasters, however, occur everywhere, and their direct costs have been increasing for the past several decades. The 2010 earthquake in Haiti was the deadliest disaster experienced for a generation, while the costliest disaster ever was the 2011 triple earthquake-tsunami-nuclear disaster in Japan.

The poor, both in low- and higher-income countries are especially vulnerable to the impact of disasters, so that disasters are not only of interest to social scientists because of society-wide economic impact, their impact on the public sector which bears the costs of reconstruction, or because of environmental impact, but also because of their importance in the process of development and income growth. The World Bank, for example, devoted its 2014 flagship publication, the *World Development Report*, to the risk faced by poor households, poor regions, and poor countries, with a special emphasis on risks that are associated with natural events. The need to understand the role of disasters and their impacts on the poor, in creating and sustaining poverty, and in generating poverty traps, is even more acute as the changes due to human-induced climate change are predicted to be more extreme in poorer countries and will thus place additional barriers to poverty alleviation.[1]

[1] There is little certainty regarding the impact of climate change on the occurrence of natural disasters, though the most recent assessment by the IPCC concludes that the frequency of days with extreme temperature, of floods, and of droughts, is likely to increase (IPCC, 2012). In addition, the spatial distribution of extreme events is likely to change leading to further impact as these will affect areas that are even less prepared for them.

The empirical and theoretical research on disasters has been evaluating the impacts of natural disasters on a diverse range of social and economic issues: the economic growth impact of disasters in the short and long terms, the fiscal impact of disasters, the impact on international trade and financial flows, the impact on populations through migration and fertility choices, the impact on human capital accumulation, the importance of political-economy in shaping the disasters' aftermath, and other related topics. The research on the impact of disaster shocks specifically on the poor is one branch of this wider 'disaster' literature that has not yet been adequately summarized, nor has there appeared to be any attempt to reach any general conclusions from the numerous case studies (country-specific, disaster-type-specific, or disaster-event-specific) that constitute the bulk of this research stream.

This lacuna is at least in part attributable to the complex nature of the inter-relationship between disaster impacts and poverty and welfare outcomes, and the consequent diversity of impacts across the investigated case studies. An additional difficulty, given this diversity of outcomes, is in identifying the precise channels - both direct and indirect - that describe the causal mechanisms.

Here, we embark on an attempt to provide some generalizations about this literature through the use of a rigorous and quantitative meta-analysis of this literature. Two strands of literature constitute our primary focus in this study. The first strand investigates the immediate (direct or first-order) effect of disasters on the poor specifically, and on society-wide poverty and household welfare measures. The second strand explores the consequent indirect (higher-order) effects that have an impact on the lives of the poor, in generating additional poverty, or in the creation and sustenance of poverty traps.[2] Given the nature of our quantitative meta-analysis, we restrict our investigation to research projects that are empirical in nature, and thus exclude, qualitative assessments, theoretical analysis, and work that relies on calibration of structural models.[3]

The diverse foci of these empirical studies and the multitude of different empirical findings clearly demonstrate the importance of synthesizing these research results in meta-regression analysis. According to guidelines suggested by Stanley et al. (2013), a statistical meta-analysis is explicitly designed to integrate econometric estimates, typically regression coefficients or transformation of regression coefficients. To put differently, a meta-analysis is a quantitative summary of statistical indicators reported in a series of similar empirical studies (e.g., Brander et al., 2006). We essentially provide an exploratory synopsis of the empirical literature analyzing the direct and indirect relationship among poverty, household welfare and natural disasters attempting to generalize from the contextual idiosyncrasies of each case-study using a meta-regression methodology.

The empirical studies utilized to conduct the quantitative analysis here illustrate the geographical coverage of this research: Asia (36.8% of research projects) and Africa (34.2%) are the most studied regions compared to Central America (23.7%), South America (18.4%) and Oceania (15.8%). Regarding the types of natural disasters studied, hydro-meteorological events (mainly floods, rainfall and tropical cyclones) are studied in 21 studies (55.2%)

[2] Cavallo and Noy (2011), following ECLAC methodology, distinguish between the direct impact of sudden-onset disasters (the immediate mortality, morbidity, and physical damage) and the indirect impact that affects the economy in the aftermath of the actual damage caused (including secondary mortality and morbidity, and an impact on economic activity). The World Bank in their survey *Natural Hazards Unnatural Disasters* (2010) employs a different terminology that makes essentially the same distinction: first-order and higher-order effects.

[3] A companion narrative review of the literature that also describes the projects that employ other methodological approaches is Karim and Noy (2014).

followed by geo-climatological events (i.e. droughts and earthquakes) in 13 studies (34.2%). The rest constitute 7 studies that investigate multiple types of natural shocks (18.4%).

The organization of this paper is as follows: Section 2 details the data construction procedure identifying first the algorithm that led to the choice of studies to include, and then providing detailed explanation of the specific categories of variables we included as both the independent and dependent variables in our regression analysis. This section follows closely the meta-analysis protocol outlined in Stanley et al. (2013). This section also includes the relevant descriptive and summary statistics. Section 3 presents the methodological framework with the specifications we use and the functional form of the meta-regression. Section 4 examines the regression output and provides interpretation of results comparing it with the results outlined in the existing literature we analyze. In Section 5, we conduct robustness checks using a sensitivity analysis with restricted observations. We end with some conclusions and a further research agenda.[4]

2. Data Construction

The empirical literature on poverty and natural disasters is relatively new with a substantial inflow of new studies during the past decade. This may be the case because of the availability of new data, the increasing media presence of natural catastrophes, and/or the potential link to the changing climate. This short history assists us in as much as almost all the studies we found were completed using rigorous statistical/econometric approaches. We attempted to collect as many empirical studies as were available.

[4] Goodman et al. (2013) describe the steps that are dictated in a standard meta-analysis protocol: "1) a thorough literature search; 2) clear and transparent eligibility criteria for selecting studies to include in the analyses; 3) a standardized approach for critically appraising studies; 4) appropriate statistical calculations to assess comparisons and trends among study findings; and 5) evaluations of potential sources of heterogeneity and bias." In this section, we describe steps (1)-(3), in the next section we describe (4), while the last two sections include detailed descriptions of the evaluations we undertook (step 5).

Our base sample constitutes English-language papers identified through an extensive search using the main relevant search engines and electronic journal databases deploying combinations of keywords and terminologies. Papers have been collected between April and June, 2013. We searched in: EconLit, Google Scholar, JSTOR, RePec, Wiley Online Library, and the World Bank working paper series. The keywords we used in these searches were: poverty and natural disasters, inequality and natural disasters, impacts of natural disasters on household, weather shocks and household welfare, and impacts of natural shocks on the poor. We followed this by examining the existing bibliographies within these papers we already identified to further widen our sample. The studies we collected range from journal articles, to project reports, book chapters and working papers.

Out of 62 studies we identified, we were able to extract 161 separate observations from 38 studies of direct and indirect impacts on poverty and welfare indicators impacted through different types of sudden and slow on-set naturally occurring events.[5] The maximum number of observations taken from a single study is 20 and the average number is 4.2. Table 1 details the list of studies we analyzed and reports the number of observations derived from each study in the finalized sample of 38 papers.

2.1 Disaster types and outcome variables: Broad and Sub-categories

Due to diverse range of foci within the available literature, we have accumulated the measures of poverty and welfare outcomes under several broad categories: income,

[5] We could not use 24 studies for our statistical analysis either because of the methodology they used (e.g., calibrated modeling), some of the data was missing in their reporting (e.g., number of observations in sample), or their focus was on evaluation of alternative coping strategies rather than impact analysis. In a companion paper (Karim and Noy, 2014), we summarize some general information from all 62 studies including a study description (author, year of publication, study area and specification of natural disaster), data sources and time period used, sample size and methodology, and the results and main conclusions of each study.

consumption, poverty, wealth, health, education and labor. Within each category, we further sub-divided the measures into separate indicators, to enable us to examine whether the type of poverty/welfare measure used affects the results. The classification of types of natural disasters and the methodologies being used were also recorded and classified for further analysis. Table 2 presents the lists of categories of variables and their descriptions. The frequency distribution of observations for each of 14 types of outcome variables is described in Table 3.

The direct and indirect impacts of disasters have mostly been defined from the perspectives of income, consumption (for direct impact) and poverty and wealth indicators (for indirect or longer-term). We have further sub-divided income and consumption into three sub-categories while leaving wealth and poverty under one broad category. The direct and indirect impacts of shocks on health, education and labor outcomes have also been investigated in some of the studies in our sample; we categorized health, education, and labor in two different sub-categories each. A comprehensive description of these sub-categories is provided in table 2.

In order to conduct our analysis, without assuming that 'all disasters are created equal', we classified three different types of disasters: disaster 1 (hydro-meteorological), disaster 2 (geo-climatological) and disaster 3 (bunched or grouped natural shocks). Table 2 provides additional information on the types of these natural shocks.

2.2 Control variables

We recorded a set of control variables for the observations in our sample. The control variables are included in a binary format based upon their usage in the selected studies; i.e., when a particular control variable had been used in a paper we have recorded 1 and when the specified model failed to control for a specific variable, we recorded 0. The set of control variables whose inclusion we recorded are household/community characteristics (i.e. household heterogeneity including characteristics regarding household head), year and seasonal effects, regional characteristics (i.e., district dummies), demographics (population and labor force characteristics), socio-economic indicators (occupation, land ownership and access to safety net) and features indicating geographical and natural-environmental features. Comprehensive descriptions of these controls are provided in table 2.

2.3 Standardization

Following the data collection from the 38 papers included in our sample, we next standardized and converted the estimates of different categories of variables taken from each study to a common metric to make them usable for a comparative meta-analysis. We calculated the percentage changes of the major indicators under representation.[6] In studies where impacts of particular type of disaster (e.g. typhoon) had been documented for various disaster strengths (e.g., Anttila-Hughes and Hsiang, 2013), we calculated the cumulative effect over the investigated horizon of a disaster of average strength.[7] The standardization also includes a sign change (+/-) with a positive (+) sign implying a positive impact on poverty and welfare outcomes due to natural disaster whereas a negative (-) sign suggesting the opposite.

[6] In cases where seasonal impacts of disasters (e.g. rainfall) had been reported (see Asiimwe and Mpuga, 2007) or index values are taken (e.g. Rodriguez-Oreggia et al, 2013) or anthropometric values are being recovered (Hoddinott and Kinsey, 2000 and 2001), we used the following measure as used in Rodriguez-Oreggia et al (2013) to extract the respective observation: PC = CV/MV *100; where PC = Percentage Change, MV = Mean Value and CV = Coefficient Value.

[7] One particular study (i.e., Baez and Santos, 2008) reported the impacts of two earthquakes making the impact magnitude of the observation higher than usual.

In Appendix Table 1 we document the descriptive statistics of all the variables used to conduct this meta-analysis. The total number of observations is 161 with the LHS variable having a mean of -2.01, a median of -0.75 and a standard deviation of 7.89; the maximum is 24.96 and the minimum is -32.23.

3. Methodological Framework

Our main objective here is to generalize the direct and indirect impacts of natural disasters on poverty and welfare outcomes. We therefore, employ the following general econometric specification:

$$y_i = \beta_i D_{\alpha i} + \delta_i x_i + \mu_i$$

Here, $D_{\alpha i}$ is the set of explanatory variables in binary format, x_i is the set of control variables also in binary format (control variables used in the selected studies) and μ_i representing the error term. β_i and δ_i are the vectors of estimated coefficients of the respective explanatory variables. The dependent variable in our regression equation is a vector of percentage change of poverty-impact estimates, labelled y_i , whose construction has been detailed in the previous section.

Heterogeneity is likely to be present due to between-study variation. The possible reasons could be differences in sample size or population, study design and methodologies employed. We therefore use White's heteroskedasticity-corrected standard errors. We also tested for multi-collinearity using and comparing various sub-sets of observation for further robustness checks.

4. Estimation results

We start with the most basic specification, estimated using ordinary least square (OLS) (with heteroskedasticity correction for the standard errors). We continued with weighted least square (WLS) estimation using the same control variable specifications as in the OLS regressions with the weights determined by the number of observations in each of the original papers we investigated (each weight corresponds to exactly the same regression from which that observation was obtained). These results are reported in table 4 and 5.

We formulated three groups to obtain four different model specifications. Model (1) includes all variables, Model (2) the outcome and shocks variables, Model (3) the outcome and the control variables and finally Model (4) includes only the outcome variables. We note that the fit (R^2) of all the models appears to be better for the WLS estimations. This, however, may be misleading since this statistic measures the ability of the estimated model to explain the variance in the weighted data.[8]

We first examine the outcome variables in table 4. For income, for example, the negative coefficient that is obtained in most specifications is interpreted to mean that when one examines the impact of disasters on income (rather than on some other outcome measure), one observes a more negative impact – in short, that disasters appear to decrease incomes more than other impact measures. This result is especially statistically pronounced for models 2 and 4 with the WLS estimation. Elsewhere, the coefficient on income is still negative, but not statistically significant. It is important to note that the magnitude of the coefficients is quite large. The largest coefficient we estimate point to a decrease in income of 11 percentage points, and most other statistically significant estimates (see table 5) are around 8-10 percentage points.

[8] See Willett and Singer (1988).

For the other short-term outcome variable, consumption, there is less of an obvious pattern, and we do not observe any robust results. This finding of a robust decrease in income, but a more uncertain impact on consumption, is the explicit conclusion arrived in many of the empirical case studies that are part of our sample.[9] More results about the types of income and consumption that are impacted are available in table 4. In general, this finding of decreased income that is larger than any impact on consumption is suggestive that, at least in part, we observe (partial) consumption smoothing through supply of *ex post* credit (formal or informal), relief support, tax relief, or other mitigation policies.

More intriguingly, the longer-term welfare measures that are sometime investigated—poverty indicators, wealth and labour market measures—all appear to be also consistently negatively affected by disasters, as can be seen in table 4. As in the case of the income measures, they appear to be more consistently negative. Both wealth tends to decrease due to a natural event and the poverty rates appear to increase (though once again the coefficients are statistically robust only in a few specifications – in this case, Model 4). There does not seem to be a similar conclusion regarding health outcomes, this might be expected as longer-term health impacts are probably only likely if the disaster shocks occurs in-vitro or during infancy and are thus much more difficult to identify.

We observe from table 4 that including regional or time controls reduces the observed adverse impact of disasters, but the inclusion of socio-economic controls does the opposite. It appears that the disaster impacts are not 'an equal opportunity menace' and that the poor are indeed more adversely affected by disasters than groups from higher socio-economic background.

[9] See Carter et al, 2007; Tesliuc and Lindert, 2002; Anttila-Hughes and Hsiang, 2013; Giesbert and Schindler, 2012; Morris et al, 2002; Asiimwe and Mpuga, 2007; Mueller and Osgood, 2009b; and Baez and Santos, 2008.

In table 5, we investigate the impact of disasters on the various outcome variables in more detail, now distinguishing between the different types of income, consumption, wealth, education and labor market indicators. We observe, for example, that while initially we concluded that indeed there is an exceptionally adverse impact of disasters on income in general, this result appears to be driven by a negative impact on INCOME3 (per capita or household income) rather than aggregate measures of total, urban, or rural income. Other types of income measures do not show this adverse impact. Similarly for consumption, any adverse impact of disasters on consumption seems to be more focused on non-food consumption. The consumption of food does not appear to be much affected, on average, according to the evidence we have. Non-food consumption might be correlated with longer-term investments (in human and social capital in particular). Education outcomes (human capital) are also now more easily distinguished in table 5. EDUC2 and HEALTH2, measuring expenditure in both education and health, both appear to be especially adversely affected by disasters; unlike alternative measures of both education accumulation and health status. Thus, spending on these decreased, but there is no evidence that outcomes, which should usually take years to manifest, have changed.[10] The results on labor market indicators mirrors this dichotomy as well. The adverse impact of disasters appears to be concentrated on prices: in this case, wages. Wages (both male and female) decline as the result of a disaster.[11] There seem to be on identifiable impact on labor force participation rates. As before, we still observe negative and statistically significant coefficients for the socio-economic controls.

[10] This result corresponds with the findings of Tiwari et al (2013) on children's weight and adult women's outcomes of Maccini and Yang (2009).

[11] This result corresponds with the findings of Mueller and Osgood (2009a), Mueller and Quisumbing (2011), Mahajan (2012), Shah and Steinberg (2012), and Chantarat et al. (2014).

The evidence on the impact of disasters on poverty, as measured by several indicators of poverty also conforms to our expectations. In most cases, poverty measures increase as a result of a disaster occurrence, (as shown in table 5). This has been primarily due to the direct impact of natural disasters globally on various forms of poverty incidences.

We find no evidence that there are large differences between the impacts of different types of disasters on poverty, income or consumption measures. We use six control variables in our estimation model namely household/community characteristics, region and time variant characteristics, demographic and socio-economic variables and geographical characteristics. Evidence from our estimation results, depicted in both models (table 4 and 5), suggests that accounting for household heterogeneity and characteristics is important in identifying disaster outcomes in case studies. The coefficients on the socio-economic and demographic variables are negative and statistically significant, indicating the importance of occupation, land ownership, population numbers, labor force characteristics, and access to safety net in the sample's studies.

We find no statistically observable difference in estimation results across the various methodological approaches adopted in this literature. Finally, the estimates regarding the disaster dummy variables mostly illustrates the comparison between the hydro-meteorological events primarily floods, rainfall and tropical cyclones and the geo-climatological events. Droughts and earthquakes are found to be have more adverse impact compare to floods and tropical storms.

5. Robustness checks

As further robustness check to examine how consistent the results are across various sub-groups, we conduct and compare our estimation results using restricted samples. In particular, we hypothesize that different disasters may have different impacts, and mirroring the debate within the literature on the short-run aggregate cost of disasters, we distinguish between these disasters that appear to create alternative dynamics (maybe through a Keynesian expansion or through institutional change) (see Skidmore and Toya, 2002, and Cavallo et al., 2013). In Table 8 (in appendix), we compare results for Model (1) that utilize all LHS observations (161 observations), Model (2) that includes all the LHS>0 observations (70 observations) and finally, Model (3) that only includes the LHS<0 observations (91 observations).

The estimations based upon the sub-samples (table 6) provide less clear implications, are only aimed at examining whether there are systematic differences between those cases in which authors observed some improved outcomes (+ sign), to those in which they found deteriorations (- sign). The results are now less robust (as the sample is reduced significantly for each sub-sample), and are less consistent. Largely, we still observe that income is affected more adversely than consumption, and that both are affected more adversely than the longer-term indicators. As before, we also observe more adverse impacts on the various measures from earthquakes and droughts compare to the hydro-meteorological events.

6. Conclusions

Natural disasters affect households adversely, in general, and they do so especially for people with lower incomes and wealth that are less able to smooth their consumption through access to post-disaster credit or assistance. We conducted a meta-regression analysis of the existing literature on the impacts of disasters on households, focusing especially on the poor and on poverty measures. We find much heterogeneity in these impacts, but several general patterns, often observed in individual case studies also emerge from the meta-analysis. Incomes are clearly impacted adversely, with the impact observed specifically in per-capita measures (so it is not due to the mortality caused by the observed disaster). Consumption is also reduced, but to a lesser extent than incomes. Importantly, poor households appear to smooth their food consumption by reducing the consumption of non-food items; the most significant items in this category are spending on housing, health, and education. This suggests potentially long-term adverse consequences as consumption of health and education services is often better viewed as long-term investment.

There are limits to what we can conclude using our methodology, especially since this meta-analysis is covering a fairly large and diverse literature. These limits are especially obvious as we note that we observe no robust insight on the impact of disasters in the longer term. It might be the case that only very large disasters impose long-term consequences on the affected, but it may also be the case that our measurements are not focused enough to enable us to identify what these outcomes are. There is, after all, significant evidence that adverse but short-term shocks can imply long term adverse consequences, especially within the context of poverty traps (World Bank, 2014).

The literature on the impact of disasters—both intensive and extensive—on the welfare of households, is growing daily. The main task is to identify the channels through which the shocks impose more costs than the immediate impacts, so that policy intervention may mitigate those, while also trying to prevent the initial losses. The observation that we consistently find non-food spending decrease in the aftermath of natural disasters is especially of concern, as it does imply to possibility of disasters preventing long-term investment and therefore trapping households in cycles of poverty.

We do believe, however, the general pattern is well established, and the need to develop the policy instruments that can deal with these dangers is clearer. One promising avenue of protecting households from the indirect impact is providing insurance, but the distribution of various insurance products, especially within the context of rural poverty in low-income countries, is facing significant challenges.

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TABLE 1: NUMBER OF OBSERVATIONS FROM THE SELECTED STUDIES

PAPER IDENTIFICATION	PAPER SOURCE	NO. OF OBSERVATIONS
1	Rodriguez-Oreggia et al (2013)	16
2	Mogues (2011)	2
3	Morris et al (2002)	2
4	Datt and Hoogeveen (2003)	2
5	Carter et al (2007)	1
6	Hoddinott and Kinsey (2001)	4
7	Reardon and Taylor (1996)	1
8	Lal et al (2009)	1
9	Jha (2006)	5
10	Wong and Brown (2011)	2
11	Silbert and Pilar Useche (2012)	3
12	Tiwari et al (2013)	4
13	Maccini and Yang (2009)	6
14	Asiimwe and Mpuga (2007)	7
15	Dercon (2004)	3
16	Glave et al (2008)	4
17	Tesliuc and Lindert (2002)	20
18	Anttila-Hughes and Hsiang (2013)	13
19	Jakobsen (2012)	2
20	Lopez-Calva and Juarez (2009)	3
21	Baez and Santos (2007)	7
22	Auffret (2003)	1
23	Skoufias et al (2012)	6
24	Mueller and Osgood (2009b)	4
25	Mueller and Quisumbing (2011)	2
26	Giesbert and Schindler (2012)	1
27	Narayanan and Sahu (2011)	1
28	Khandker (2007)	1
29	Mahajan (2012)	2
30	Foltz et al (2013)	4
31	Shah and Steinberg (2012)	10
32	Thomas et al (2010)	4
33	Hou (2010)	2
34	Hoddinott (2006)	4
35	Hoddinott and Kinsey (2000)	4
36	Jensen (2000)	4
37	Baez and Santos (2008)	2
38	Mueller and Osgood (2009a)	1

Source: Authors' Calculations

TABLE 2: LISTS OF CATEGORIES OF VARIABLES AND THEIR DESCRIPTIONS

CATEGORIES	DESCRIPTION OF VARIABLES
Income 1	Farm/Agricultural/Rural income
Income 2	Non-Farm/Entrepreneurial/Urban income
Income 3	Total Household Income
	Per Capita Income
	Total Income Loss
Consumption 1	Household Consumption/Expenditure
	Per Capita Consumption/Expenditure
	Rural Consumption /rural per capita consumption
	Urban Consumption
	Consumption Growth/CECG
Consumption 2	Food Consumption/Expenditure
Consumption 3	Non-Food Consumption/Expenditure
Poverty	Poverty Incidence
	Food Poverty Incidence
	Asset Poverty Incidence
	Capacities Poverty Incidence
	Poverty Rate
	Human Development Index
Wealth	Total livestock asset
	Asset Index
	Agricultural Productive Asset Index
	Non-Productive Asset Index
	Asset Growth
	Asset Loss
Health 1	Child Height (cm), cohort 1 - 12-24m
	Child Height (cm), cohort 2 - 24-36m
	Child Height (cm), cohort 3 - 36-48m
	Child Height (cm), cohort 4 - 48-60m
	Child Weight (kilo), cohort 1 - 12-24m
	Child Weight (kilo), cohort 2 - 24-36m
	Child Mortality , CM (female)
	Malnourishment/malnutrition (by gender), MAL (rural HH)
	Adult (women) height (cm)
	Body Mass Index (men)
	Body Mass Index (women)/mother
Health 2	Health Expenditure

Education 1	Completed Grades of Schooling
	School Attendance, SA (rural HH)
	School Enrolment by gender
Education 2	Educational Expenditure
Labor 1	Agricultural/Farm/Rural wage
	Non-Farm/Urban wage
	Male wage
	Female wage
Labor 2	Labor Force Participation-male
	Labor Force Participation-female
	Child Labor Force Participation/ CLFP (rural HH)
Household / Community Characteristics	Household heterogeneity
	Community/ village level heterogeneity and characteristics (e.g. access to roads, markets)
	Head of HH's education, age, gender, marital status, employment status
	HH size
	HH composition (e.g. number of adult male/female members, no. of children)
	Control regarding HH level data limitation
	Ethnicity
Time variant characteristics	Time fixed effect
	Seasonal Fixed effect
	Survey year fixed effect
	Birth year-season, birth district-season and season specific linear time trends
Regional characteristics	Region /District/Province fixed effect
	Municipality fixed effect
Demographic	Life-cycle age of Households
	Population characteristics in general
	Labor force characteristics
Socio-Economic	HH ownership of business, land, animals
	Occupation (e.g. farm/non-farm)
	Asset (e.g. access to electricity, water, sanitation, healthcare, credit, banks, savings)
	Pre-shock HH income/asset value
	Post-shock inheritance

Geography / Nature	Natural and geographical characteristics (e.g. measures of latitude, altitude, surface length, avg. temp. and rainfall (max/min))
	Precipitation rate
	Earth shaking distribution
Disaster 1	Flood / riverine flood
(Hydro-Meteorological)	Rains / rainfall shocks
	Positive rainfall including seasonal deviation
	Negative Rainfall including variability (e.g. delay of monsoon / post on-set low rainfall)
	Hurricane/Storms/Cyclone/Tornado/Typhoon
	Tsunami
Disaster 2	Frost
(Geo-Climatological)	Drought / dry spell including time horizons (1-5 years ago/6-10 years ago)
	Earthquake
	Forest Fire
	Volcanic eruptions
Disaster 3	Bunched natural shocks
(Groups)	
Method 1	Linear regression
	Logistic regression
	Multinomial /multivariate (logit) regression
	Time series non-linear regression
	Difference in difference regression
	Reduced-form linear regression / reduced form log-linear regression
	Log linear regression
	Dynamic model using regression
	Multivariate Probit regression
	Recursive bivariate probit model
Method 2	Foster-Greer-Thorbecke (FGT) poverty index
	Macroeconomic aggregates corresponding to ND
	Income source decomposition
	Case study analysis, group interviews
	Cluster analysis

Source: Authors' elaborations

TABLE 3: FREQUENCY DISTRIBUTION OF OBSERVATIONS IN OUTCOME VARIABLES

OUTCOME VARIABLES	NO. OF OBSERVATIONS
INCOME 1	5 (3.1)
INCOME 2	6 (3.7)
INCOME 3	10 (6.2)
CONSUMPTION 1	39 (24.2)
CONSUMPTION 2	9 (5.6)
CONSUMPTION 3	4 (2.5)
POVERTY	20 (12.4)
WEALTH	9 (5.6)
HEALTH 1	27 (16.8)
HEALTH 2	2 (1.2)
EDUCATION 1	9 (5.6)
EDUCATION 2	1 (0.6)
LABOR 1	14 (8.7)
LABOR 2	6 (3.7)

Source: Authors' Calculations

Note: The numbers in parenthesis shows the percentage of number of observations against the corresponding variable.

TABLE 4: META-REGRESSION RESULTS A: THE DIRECT AND INDIRECT IMPACTS

	(1)		(2)		(3)		(4)	
VARIABLES	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
INCOME	-2.503	-3.247	-2.753	-11.90**	1.856	-0.921	-1.818	-8.431***
	(4.606)	(6.254)	(3.866)	(5.889)	(3.648)	(5.247)	(2.434)	(1.491)
CONSUMPTION	2.365	0.498	-0.193	-7.772	6.081*	2.934	0.0956	-3.589
	(4.005)	(5.669)	(3.393)	(5.621)	(3.409)	(4.008)	(0.948)	(2.564)
POVERTY	-1.677	-1.767	-3.378	-9.720	2.651	1.142	-2.475**	-3.637**
	(4.287)	(7.197)	(3.583)	(7.186)	(3.188)	(4.398)	(1.021)	(1.591)
WEALTH	-5.398	-2.632	-5.704	-4.794	-0.632	-0.0883	-4.808**	-1.371
	(4.543)	(6.560)	(3.850)	(5.764)	(3.563)	(4.950)	(1.949)	(1.386)
HEALTH	0.711	3.022	-3.112	-6.502	5.251	5.137	-2.466**	-2.987
	(3.606)	(6.885)	(3.566)	(6.555)	(3.580)	(5.967)	(1.110)	(2.912)
LABOR	-3.459	-2.556	-6.368*	-8.288	0.725	-0.0584	-5.642***	-4.994**
	(3.811)	(7.266)	(3.821)	(5.784)	(4.034)	(5.856)	(1.689)	(2.092)
HH/COMMUNITY	-5.115*	-1.064			-4.936*	-2.814		
	(2.766)	(4.059)			(2.559)	(3.455)		
TIME	0.0902	7.155**			0.409	5.902***		
	(1.445)	(2.811)			(1.490)	(2.189)		
REGION	2.839	3.839			3.612**	4.941**		
	(1.735)	(2.998)			(1.487)	(2.175)		
DEMOGRAPHIC	-2.668	-2.037			-2.731	-0.702		
	(1.966)	(4.398)			(1.932)	(4.448)		
SOCIOECONOMIC	-4.402***	-11.69***			-3.921***	-9.991***		
	(1.429)	(2.690)			(1.277)	(2.470)		
GEOG/NATURE	-2.616	-5.773***			-2.662*	-6.632**		
	(1.600)	(2.110)			(1.563)	(2.579)		
METHOD_1	4.779	4.652	1.752	3.168				
	(4.339)	(6.056)	(3.346)	(5.223)				
DIS_1	0.658	-3.589	-1.283	0.347				

	(5.581)	(2.819)	(1.298)	(2.633)				
DIS_2	1.467							
	(5.499)							
DIS_3	-0.499	-1.066	-2.712	6.149				
	(5.549)	(5.091)	(3.307)	(5.451)				
EDUCATION		-3.466	-1.998	-4.810	4.313	-1.042	-1.401	-1.296
		(8.418)	(5.497)	(6.406)	(5.339)	(7.495)	(4.314)	(2.576)
OBSERVATIONS	161	161	161	161	161	161	161	161
R^2- ADJUSTED	0.1863	0.3408	0.0705	0.2284	0.1838	0.3434	0.0760	0.2345

Source: Authors' Calculations

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

Table 5: Meta-Regression results B: the direct and indirect impacts

	(1)	(2)			(3)		(4)	
Variables	**OLS**	**WLS**	**OLS**	**WLS**	**OLS**	**WLS**	**OLS**	**WLS**
income_1	10.95		13.48	6.850***	8.092***	8.059**	5.820***	5.820***
	(11.13)		(11.34)	(2.037)	(3.097)	(3.983)	(1.277)	(1.277)
income_2	11.00	-5.420	13.00	-3.049	8.058*	1.599	5.290	-4.596**
	(11.65)	(3.342)	(11.93)	(2.548)	(4.475)	(4.968)	(3.684)	(2.171)
income_3	-2.911	-10.66***	-2.108	-8.754***	-6.156*	-3.739	-9.901***	-10.29***
	(11.25)	(3.119)	(11.63)	(1.763)	(3.139)	(4.843)	(2.900)	(1.101)
consume_1	9.011	-3.071	9.805	-0.272	5.206*	4.124	0.829	-1.385
	(11.04)	(2.465)	(11.30)	(3.444)	(3.039)	(3.354)	(1.101)	(2.485)
consume_2	4.679	-12.91***	3.591	-11.14***	1.626	-5.783	-4.194**	-12.66***
	(11.29)	(3.792)	(11.45)	(2.635)	(3.869)	(5.303)	(2.121)	(2.325)
consume_3	13.37	4.691	10.42	3.543	10.34**	12.18**	2.593	2.257
	(11.41)	(5.474)	(11.55)	(2.148)	(4.123)	(5.082)	(2.574)	(1.590)
poverty	4.819	-2.841	5.606	-4.208	1.507	4.127	-2.475**	-3.637**
	(11.29)	(5.324)	(11.30)	(3.494)	(2.652)	(4.451)	(1.045)	(1.629)
wealth	1.479	-5.657	2.977		-1.597	0.925	-4.808**	-1.371
	(11.28)	(4.170)	(11.43)		(3.446)	(3.828)	(1.994)	(1.418)
health_1	8.574	0.150	5.811	1.533	5.494*	6.955	-2.061**	-0.105
	(11.13)	(3.319)	(11.28)	(1.535)	(3.188)	(4.930)	(0.843)	(0.0645)
educ_1	9.450	5.072	8.754	2.581	6.285	12.06**	0.866	0.944
	(11.55)	(3.678)	(12.04)	(1.774)	(4.834)	(5.018)	(4.221)	(0.885)
educ_2	-13.20	-21.74***	-13.86	-20.16***	-16.56***	-14.91***	-21.80	-21.80***
	(11.02)	(3.340)	(11.25)	(1.535)	(3.392)	(5.007)	(0)	(0)
labor_1	2.115	-3.587	1.390	-5.397*	-1.043	3.670	-6.418***	-6.226**
	(11.25)	(4.242)	(11.41)	(3.032)	(3.525)	(4.786)	(1.868)	(2.490)
labor_2	6.913	4.153	4.107	1.491	3.655	11.04*	-3.833	-0.148
	(11.87)	(4.939)	(11.84)	(3.722)	(5.495)	(6.002)	(3.653)	(3.356)
hh/community	-5.563**	-3.006			-5.762**	-4.792		
	(2.549)	(3.201)			(2.373)	(2.902)		
time	1.482	5.610*			1.526	4.122*		
	(1.398)	(2.839)			(1.469)	(2.179)		
region	3.227*	2.700			3.490**	2.553		

	(1.714)	(3.835)			(1.453)	(2.106)		
DEMOGRAPHIC	-4.216**	-9.358***			-4.257**	-8.196***		
	(1.667)	(2.285)			(1.643)	(2.105)		
SOCIOECONOMIC	-1.705	-5.174***			-1.541	-3.826**		
	(1.342)	(1.944)			(1.252)	(1.880)		
GEOG/NATURE	-2.809*	-4.227			-2.956*	-4.948*		
	(1.634)	(2.572)			(1.565)	(2.913)		
METHOD_1	0.643	7.515	-0.0727	3.925				
	(3.619)	(5.426)	(3.108)	(5.142)				
DIS_1	-3.878	-3.473	-7.867	-5.564				
	(11.46)	(2.368)	(11.67)	(5.355)				
DIS_2	-3.142		-7.403	-4.549				
	(11.41)		(11.66)	(5.728)				
DIS_3	-5.693	-0.772	-11.36	-1.349				
	(11.42)	(4.875)	(11.37)	(3.727)				
HEALTH_2		-22.89***		-21.31***	-3.411	-16.05***	-7.940	-22.94***
		(3.340)		(1.536)	(11.27)	(5.005)	(11.13)	(0.0523)
METHOD_2		5.218						
		(5.591)						
OBSERVATIONS	161	161	161	161	161	161	161	161
R^2- ADJUSTED	0.3163	0.6911	0.2394	0.6647	0.3234	0.6903	0.2399	0.6674

Source: Authors' Calculations
Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

TABLE 6: META-REGRESSION RESULTS WITH RESTRICTED OBSERVATIONS

	ALL OBSERVATIONS		ALL POSITIVE OBSERVATIONS		ALL NEGATIVE OBSERVATIONS	
VARIABLES	OLS	WLS	OLS	WLS	OLS	WLS
INCOME_1	10.95		-9.726*	3.453		
	(11.13)		(5.245)	(2.373)		
INCOME_2	11.00	-5.420	-7.846	5.333	15.04***	-7.420***
	(11.65)	(3.342)	(5.953)	(4.484)	(4.31e-07)	(2.101)
INCOME_3	-2.911	-10.66***	-12.55***	1.524	10.14***	-11.78***
	(11.25)	(3.119)	(4.396)	(1.749)	(3.292)	(2.275)
CONSUME_1	9.011	-3.071	-10.60**	2.187	19.08***	-10.32***
	(11.04)	(2.465)	(4.882)	(1.782)	(1.760)	(2.900)
CONSUME_2	4.679	-12.91***	-11.19**	0.367	14.43***	-14.83***
	(11.29)	(3.792)	(5.482)	(2.514)	(2.529)	(2.385)
CONSUME_3	13.37	4.691	-10.16*	-0.301	20.53***	
	(11.41)	(5.474)	(5.931)	(2.098)	(1.309)	
POVERTY	4.819	-2.841	-15.19***	-3.602*	17.99***	-7.701*
	(11.29)	(5.324)	(4.658)	(1.911)	(2.486)	(4.110)
WEALTH	1.479	-5.657	-15.98***	-4.160*	14.29***	-11.20***
	(11.28)	(4.170)	(5.058)	(2.218)	(2.447)	(3.980)
HEALTH_1	8.574	0.150	-11.78*	5.077	19.77***	-0.802
	(11.13)	(3.319)	(6.402)	(3.919)	(1.321)	(2.102)
EDUC_1	9.450	5.072	-2.626	8.143*	15.18***	1.032
	(11.55)	(3.678)	(6.682)	(4.177)	(2.499)	(4.207)
EDUC_2	-13.20	-21.74***				-22.46***
	(11.02)	(3.340)				(2.101)

LABOR_1	2.115	-3.587	-12.69**	-0.462	13.23***	-8.885**
	(11.25)	(4.242)	(4.890)	(1.466)	(2.352)	(4.248)
LABOR_2	6.913	4.153	-4.485	12.45**	13.43***	-4.520
	(11.87)	(4.939)	(8.022)	(5.663)	(3.230)	(4.488)
HH/COMMUNITY	-5.563**	-3.006	-4.353**	-6.548**	-1.545	-3.896
	(2.549)	(3.201)	(2.115)	(2.645)	(2.636)	(4.952)
TIME	1.482	5.610*	-3.138**	-8.147***	2.126	4.060*
	(1.398)	(2.839)	(1.443)	(1.749)	(1.309)	(2.101)
REGION	3.227*	2.700	0.173	-0.415	2.523*	1.770
	(1.714)	(3.835)	(2.284)	(1.999)	(1.362)	(2.034)
DEMOGRAPHIC	-4.216**	-9.358***	-2.197	-3.855	-2.112	-5.960**
	(1.667)	(2.285)	(2.048)	(2.867)	(1.777)	(2.550)
SOCIOECONOMIC	-1.705	-5.174***	0.631	4.236***	-1.045	-3.730
	(1.342)	(1.944)	(1.970)	(1.419)	(1.305)	(2.978)
GEOG/NATURE	-2.809*	-4.227	0.787	3.156**	-1.927	-4.831**
	(1.634)	(2.572)	(1.835)	(1.235)	(1.642)	(1.908)
METHOD_1	0.643	7.515	19.74***	21.73***	-2.732	10.81
	(3.619)	(5.426)	(5.085)	(4.387)	(2.345)	(7.386)
DIS_1	-3.878	-3.473	-0.0218	-11.90***	-19.20***	-3.524*
	(11.46)	(2.368)	(1.462)	(4.332)	(3.371)	(2.051)
DIS_2	-3.142			-12.73***	-18.37***	
	(11.41)			(4.655)	(2.639)	
DIS_3	-5.693	-0.772	15.55***	4.960*	-22.96***	-3.249
	(11.42)	(4.875)	(3.997)	(2.700)	(3.638)	(2.744)
HEALTH_2		-22.89***	-9.064*		-1.180***	-23.64***
		(3.340)	(4.744)		(5.63e-07)	(2.101)

METHOD_2		5.218				12.48**
		(5.591)				(6.017)
OBSERVATIONS	161	161	70	70	91	91
R^2- ADJUSTED	0.3163	0.6911	0.6026	0.6753	0.6764	0.8538

Source: Authors' Calculations
Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 1: Descriptive Statistics of Variables Defined

Variables	Observation	Mean	Median	Std. Dev.	Min	Max
Y	161	-2.014573	-0.75	7.889249	-32.23	24.96
N	161	28076.38	3823	69540.15	94	446780
INCOME	161	0.2919255	0	0.8111701	0	3
INCOME_1	161	0.0310559	0	0.1740101	0	1
INCOME_2	161	0.0372671	0	0.1900065	0	1
INCOME_3	161	0.0621118	0	0.2421116	0	1
CONSUMPTION	161	0.4285714	0	0.7133923	0	3
CONSUME_1	161	0.242236	0	0.4297732	0	1
CONSUME_2	161	0.0559006	0	0.2304465	0	1
CONSUME_3	161	0.0248447	0	0.1561374	0	1
POVERTY	161	0.1242236	0	0.3308656	0	1
WEALTH	161	0.0559006	0	0.2304465	0	1
HEALTH	161	0.1925466	0	0.4259626	0	2
HEALTH_1	161	0.1677019	0	0.374767	0	1
HEALTH_2	161	0.0124224	0	0.1111068	0	1
LABOR	161	0.1614907	0	0.4596279	0	2
LABOR_1	161	0.0869565	0	0.2826505	0	1
LABOR_2	161	0.0372671	0	0.1900065	0	1
EDUCATION	161	0.068323	0	0.2766818	0	2
EDUC_1	161	0.0559006	0	0.2304465	0	1
EDUC_2	161	0.0062112	0	0.078811	0	1
HH/COMMUNITY	161	0.8012422	1	0.4003104	0	1
TIME	161	0.6708075	1	0.4713862	0	1
REGION	161	0.757764	1	0.4297732	0	1

DEMOGRAPHIC	161	0.3664596	0	0.4833405	0	1
SOCIOECONOMIC	161	0.621118	1	0.4866223	0	1
GEOG/NATURE	161	0.5403727	1	0.4999224	0	1
METHOD	161	1.037267	1	0.1900065	1	2
METHOD_1	161	0.9627329	1	0.1900065	0	1
METHOD_2	161	0.0372671	0	0.1900065	0	1
DISASTER	161	1.459627	1	0.6613791	1	3
DIS_1	161	0.6335404	1	0.4833405	0	1
DIS_2	161	0.2732919	0	0.44704	0	1
DIS_3	161	0.0931677	0	0.2915742	0	1

Source: Authors' Calculations