



## Poverty and Natural Disasters: A Meta-Regression Analysis

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**Abstract:** With a meta-regression analysis of the existing literature on the impacts of disasters on households, we observe several general patterns. Incomes are clearly impacted adversely, with the impact observed specifically in per-capita measures. Consumption is also reduced, but to a lesser extent than incomes. Poor households appear to smooth their food consumption by reducing the consumption of non-food items; in particular health and education, and this suggests potentially long-term adverse consequences. Given the limits of our methodology and the paucity of research, we find no consistent patterns in long-term outcomes. We end by placing disaster risk for the poor within the discussions of sustainable development and future climatic change.


JEL classification: I3; Q54; Q56; B41

Keywords: disaster, natural, poverty, meta-analysis

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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 financial costs have been increasing for the past several decades.

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 their environmental impact, but also because of their importance in the processes of development, income growth, and income distribution. The World Bank, for example, devoted its 2014 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.<sup>1</sup>

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

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<sup>1</sup> 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 less prepared for them.

the causal mechanisms. We aim to fill this lacuna using meta-regression analysis.

For readers who are not familiar with this methodology, meta-regression analysis is a statistical method, a regression that is used to evaluate a body of empirical research that is itself typically regression-based. It is especially appropriate for questions for which there are multiple studies using similar methodologies, but different datasets, different regression specifications, or different time-periods. Meta-regression analysis is a companion method to a narrative survey of the literature. It identifies empirical regularities in the investigated body of work that are more difficult to spot or to rigorously establish. It further establishes what characteristics of the data, the method, or the studies' designs are most closely associated with the observed empirical regularities. Stanley (2001) provides further details about the justification and the theoretical underpinning of the meta-regression method.

Here, we embark on an attempt to provide some generalizations about this literature through the use of a meta-regression 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 household welfare, on the poor specifically, and on society-wide incidence of poverty. 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.<sup>2</sup> 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 analyses, and work that relies on calibration of structural models.<sup>3</sup>

The diverse foci of these empirical studies and the multitude of different empirical findings clearly demonstrate the importance of synthesizing these research results formally in meta-regression analysis. According to guidelines suggested by Stanley et al. (2013), a statistical meta-regression 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; previous well-known examples include Card and Krueger (1995), Smith and Huang (1995), Brander et al. (2006), and Disdier and Head (2008); recent examples are Anderson et al. (2016) and Havranek et al. (2016). We essentially provide an exploratory synopsis of the empirical literature

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<sup>2</sup> Cavallo and Noy (2011), following the ECLAC (1991) 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 on economic activity). The World Bank, in its survey *Natural Hazards Unnatural Disasters* (2010), employs a different terminology that makes essentially the same distinction: first-order and higher-order effects.

<sup>3</sup> A companion narrative review of the literature that also describes the projects that employ other methodological approaches is Karim and Noy (2016).

analyzing the direct and indirect relationship among poverty, household welfare and natural disasters attempting to generalize from the contextual idiosyncrasies of each case-study.

Our contribution here is the synthesis of the microeconomic literature examining the heterogeneity of impact of disasters on the poor, using regression meta-analysis methodology. Two recently published papers, Lazzaroni and van Bergeijk (2014) and Klomp and Valckx (2014), both conducted regression meta-analysis of the macroeconomic literature. They both focus on the impact of natural disasters on aggregate growth and conclude that while the average indirect short-term impact is largely negative, there is significant heterogeneity across countries, time periods, and types of events. Our contribution, therefore, provides useful microeconomic detail complementing the macroeconomic insights derived from this previous work.

The empirical studies utilized to conduct the quantitative analysis here illustrate the geographical coverage of this research: Asia (36.8 percent of research projects) and Africa (34.2 percent) are the most studied regions compared to Central America (23.7 percent), South America (18.4 percent) and Oceania (15.8 percent). Regarding the types of natural disasters studied, hydro-meteorological events (mainly floods, rainfall and tropical cyclones) are studied in 21 studies (55.2 percent) followed by geo-climatological events (i.e. droughts and earthquakes) in 13 studies (34.2 percent). The rest constitute seven studies that investigate multiple types of natural shocks (18.4 percent).

The organization of this paper is as follows. Section 2 details the data construction procedure. We first identify 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. We describe robustness checks with restricted samples in Section 5 and end with some conclusions and a further research agenda in Section 6.<sup>4</sup>

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<sup>4</sup> 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).

## 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 reporting 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. In order to make sure our results are less biased than a more informal qualitative survey, we include every single paper that we found by following a well-defined procedure, and which includes all the relevant variables/measures we require for our statistical analysis. In our final sample of 38 papers, 28 had gone through a peer-reviewing process. In order to attenuate any publication bias we also included working papers and other unpublished work we found while following our search procedure described below.<sup>5</sup>

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.<sup>6</sup> The maximum number of observations taken from a single study is 20 and the average number is 4.2. Table 1

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<sup>5</sup> Unlike practice in some other research disciplines, in economics most research projects are posted online as working papers long before they are accepted for publication anywhere. Thus, by relying also on search engines that identify working papers we overcome much of the publication bias that could be a bigger concern had we not been able to access unpublished research.

<sup>6</sup> We could not use 24 studies for our statistical analysis either because of the methodology they used (e.g., calibrated modelling), 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, 2016), 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.

details the list of studies we analyzed and reports the number of observations derived from each study in the finalized sample of 38 papers.

**Table 1. Number of Observations from the Selected Studies**

Paper identification	Paper source	No. of observations	Range of estimated values
1	Rodriguez-Oreggia et al. (2013)	16	(-4.2 1.28)
2	Mogues (2011)	2	(-4.5 -4.3)
3	Morris et al. (2002)	2	(-17.6 -9.7)
4	Datt and Hoogeveen (2003)	2	(-7.56 -5.02)
5	Carter et al (2007)	1	(-5)
6	Hoddinott and Kinsey (2001)	4	(-1.727 0.068)
7	Reardon and Taylor (1996)	1	(-9.15)
8	Lal et al. (2009)	1	(-6.9)
9	Jha (2006)	5	(-6.976 0.986)
10	Wong and Brown (2011)	2	(2.01 7.37)
11	Silbert and Pilar Useche (2012)	3	(-5 22)
12	Tiwari et al. (2013)	4	(-0.1 1.6)
13	Maccini and Yang (2009)	6	(0.027 24.96)
14	Asiimwe and Mpuga (2007)	7	(-3.08 0.477)
15	Dercon (2004)	3	(-6.08 -2.78)
16	Glave et al. (2008)	4	(-16.1 -6.8)
17	Tesliuc and Lindert (2002)	20	(0.1 22.2)
18	Anttila-Hughes and Hsiang (2013)	13	(-22.98 1.69)
19	Jakobsen (2012)	2	(-9.4 -5.6)
20	Lopez-Calva and Juarez (2009)	3	(-12 -2)
21	Baez and Santos (2007)	7	(-14.7 3.5)
22	Auffret (2003)	1	(-9)
23	Skoufias et al. (2012)	6	(-13.2 10.3)
24	Mueller and Osgood (2009b)	4	(-17.9 -0.3)
25	Mueller and Quisumbing (2011)	2	(-13.2 -2.8)
26	Giesbert and Schindler (2012)	1	(3)
27	Narayanan and Sahu (2011)	1	(7.1)
28	Khandker (2007)	1	(0.00169)
29	Mahajan (2012)	2	(2.4 3.6)
30	Foltz et al. (2013)	4	(1.64 2.5)
31	Shah and Steinberg (2012)	10	(-16 11)
32	Thomas et al. (2010)	4	(1.85 6.49)
33	Hou (2010)	2	(-3 -1)
34	Hoddinott (2006)	4	(-7.9 3)
35	Hoddinott and Kinsey (2000)	4	(-11.5 -0.6)
36	Jensen (2000)	4	(-14 -4.5)
37	Baez and Santos (2008)	2	(-32.23 -7.29)
38	Mueller and Osgood (2009a)	1	(-14.8)

Note: The range of the estimated values (column 4) shows the minimum and maximum of the values (in percentage terms) taken from studies under investigation.

## 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, 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 used were also recorded and classified for further analysis. Table 2 presents the lists of categories of variables and their descriptions.

**Table 2. List of Categories of Variables and their Descriptions**

Categories	Description of variables
Income 1	Farm/Agricultural/Rural income Non-Farm/Entrepreneurial/Urban income
Income 2	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 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	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 Expenditure
Education	Completed Grades of Schooling School Attendance, SA (rural HH) School Enrolment by gender Educational Expenditure

Categories	Description of variables
Labor	Agricultural/Farm/Rural wage Non-Farm/Urban wage Male wage Female wage 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 (Hydro-Meteorological)	Flood / riverine flood 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 (Geo-Climatological)	Frost Drought / dry spell including time horizons (1-5 years ago/6-10 years ago) Earthquake Forest Fire Volcanic eruptions
Disaster 3 (Groups)	Bunched natural shocks



Categories	Description of variables
Method	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 Foster-Greer-Thorbecke (FGT) poverty index Macroeconomic aggregates corresponding to ND Income source decomposition Case study analysis, group interviews Cluster analysis

Source: Authors' elaborations

The frequency distribution of observations and the descriptive statistics of for each of nine (9) types of outcome variables is described in Table 3. Among the outcome values (in percentage changes), consumption1 displays the maximum number of observations (39) followed by health (29), poverty (20), and labor (20). Interestingly, the number of negative outcomes in these categories is 16 (consumption1), 19 (health), 12 (poverty) and 15 (labor).

This skewness of the observations suggests the presence of heterogeneous impacts among the poverty-disaster outcome measures in this literature.

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 two 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 classified health, education, and labor in one category each.

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 (grouped natural shocks). Table 2 provides additional information. Information on our procedure for standardizing the dependent variables is available in the appendix.

**Table 3. Frequency Distribution of Observations in Outcome Variables**

Outcome Variables	No. of Observations <sup>a</sup>	Mean	Std. Dev.	Number of negative outcome	Min	Max
Income 1	11 (6.8)	5.53	6.96	1	-6.76	22.2
Income 2	10 (6.2)	-9.90	9.24	9	-32.23	.477
Consumption 1	39 (24.2)	0.83	6.66	16	-11.66	22
Consumption 2	13 (8.0)	-2.11	6.81	7	-15.04	10.3
(non)Poverty <sup>b</sup>	20 (12.4)	-2.47	4.58	12	-16.1	1.28
Wealth	9 (5.6)	-4.81	6.06	6	-17.6	3
Health	29 (18.0)	-2.47	5.95	19	-22.98	7.1
Education	10 (6.2)	-1.40	14.06	6	-21.8	24.96
Labour	20 (12.4)	-5.64	7.58	15	-17.9	11

Source: Authors' calculations.

Notes: <sup>a</sup> The numbers in parenthesis shows the percentage of number of observations against the corresponding variable; <sup>b</sup> As we have changed the sign due to standardization, we use non(poverty) for ease of reading.

## 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 all these controls are provided in Table 2. In Appendix Table 1 we document the descriptive statistics of all the variables used to conduct this meta-analysis.

### 3 Methodological Framework

Our main objective here is to generalize the direct and indirect impacts of natural disasters on households, poverty and welfare measures. We employ the following general econometric specification:  $y_i = \alpha C_i + \beta D_i + \delta x_i + \mu_i$ . The dependent variable in our regression equation is a vector of percentage change of disaster-impact indicators, labeled  $y_i$ . From each study, we collected the estimated impacts that disasters had on the variables of interest (e.g., household consumption, agricultural income etc.). We calculate the estimated impact in percentage change from the baseline average for this variable. So, for example, if a paper estimated that household income was reduced by 100 USD, and average household income in that sample is 1000 USD, the estimated impact is -10%, for this variable (household income) and this specific study. These are the LHS variables in our estimations.

$C_i$  is the vector of outcome variables that are potentially examined in each paper  $i$ .  $D_i$  is the set of shock variables (disaster and methodology) variables in binary format measured in each study  $i$ , while  $x_i$  is the set of control variables included in the regressions of the original studies, all these are also in binary format.  $\mu_i$  represents the error term; we assume the error terms are clustered by study.  $\alpha$ ,  $\beta$ , and  $\delta$  are the vectors of estimated coefficients.

Heterogeneity in the precision of estimates is likely to be present due to between-study variation. Possible reasons could be differences in sample size or population, study design and methodologies employed. We therefore estimate the model with standard errors clustered by study.<sup>7</sup>

We start with the most basic specification, estimated using ordinary least squares (OLS) with standard errors clustered by study. We continued with weighted least squares (WLS) estimation using the same control variable specifications as in the OLS regressions. The weights are determined by the square root of the number of observations in each of the original papers we investigated. Basing the weights on the square root of the sample size allows us not to place undue weight on the few studies with very large number of observations.<sup>8</sup>

### 4 Estimation Results

Our meta-regression results are reported in Table 4. We formulated three groups to obtain four different model specifications. Model (1) includes only the outcome variables, Model (2) the outcome and control

<sup>7</sup> Cipollina and Salvatici (2010), in their meta-analysis on reciprocal trade agreements, used clustered standard errors (by study). We also estimated the model without the clustered errors; results are very similar and are available upon request.

<sup>8</sup> Longhi et al. (2010), in their meta-study on the impact of immigration on employment and wages, adopted the technique of weighted least square with weights based on the square root of the sample size.

variables, Model (3) the outcome and the shock variables and finally Model (4) includes all the outcome variables.<sup>9</sup>

In Table 4, we investigate the impact of disasters on the various outcome variables in more detail, distinguishing between the different types of income and consumption. For per capita or household income (*income\_2*), we obtain a negative coefficient in most specifications when compared with aggregate measures of total, urban, or rural income – though the coefficient is only sometimes statistically significant using the standard thresholds. We note that agricultural income (*income\_1*) increases, relative to other measures, in the post-disaster period. In this case, a negative coefficient is interpreted to mean that the impact of disasters on per capita income (rather than on other outcome measures) is more negative.

When compared to the average impact on other outcome measures, per capita income is impacted more adversely, by 2.9-9.9 percentage point, depending on the estimated model. Disasters appear to decrease per capita income more (in percentage terms) than other impact measures such as consumption. While the coefficient on household income is mostly negative and the coefficient on consumption is generally positive, they are not statistically different from zero in all the models we estimate. It is important to note, however, that the coefficients are at times quite large, even if they are imprecisely estimated. The largest statistically significant coefficient we estimate point to an increase of consumption of 6.8 percentage points, *ceteris paribus*, relative to other variables of interest. But, overall, the results for consumption are rather less economically and statistically significant than for income. For consumption, the relatively milder (or less consistent) impact of disasters on consumption focused on per capita consumption (*consume\_1*) when compared with aggregate measures of food and non-food consumption (*consume\_2*). It is impossible to robustly compare the impacts of food and non-food consumption measures in further disaggregation due to the limited number of observations (limited number of research projects that examined these outcome variables).

This finding of a larger decrease in income, relative to consumption, in a post-disaster environment is the explicit conclusion arrived in several of the empirical case studies that are part of our sample.<sup>10</sup> In general, this finding of decreased income that is larger than any impact on consumption is suggestive that, at least in part, households and individuals are able to realize (partial) consumption smoothing through the supply of ex post credit (formal or informal), relief support, tax relief, or other mitigation policies.

<sup>9</sup> Model 4 excludes the education control because of multicollinearity.

<sup>10</sup> See Carter et al. (2007); Tesliuc and Lindert (2002); Anttila-Hughes and Hsiang (2013); Giesbert and Schindler (2012); Morris et al. (2002); Asimwe and Mpuga (2007); Mueller and Osgood (2009b); and Baez and Santos (2008).

**Table 4. Meta-regression Results: The Direct and Indirect Impacts**

Variables	(1)		(2)		(3)		(4)		
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS	
Outcome Variables	Income_1	5.531*** (1.643)	2.129 (4.46)	8.519** (3.215)	5.04 (3.621)	10.25*** (2.753)	5.06 (5.012)	4.714 (4.451)	3.481 (3.018)
	Income_2	-9.901*** (3.623)	-9.365*** (2.014)	-5.17 (4.463)	-2.945 (4.383)	-5.087 (4.415)	-6.388** (2.875)	-8.548 (5.833)	-3.797 (3.637)
	Consume_1	0.829 (1.615)	0.193 (1.809)	5.779 (3.525)	4.996 (3.169)	6.829** (2.563)	3.475 (3.078)	3.075 (4.462)	4.732 (3.435)
	Consume_2	-2.106 (1.8)	-5.848 (4.17)	5.163 (4.111)	2.341 (4.771)	2.713 (2.802)	-2.905 (4.681)	1.449 (4.897)	0.39 (3.28)
	Poverty	-2.475 (1.662)	-2.241 (1.489)	1.424 (3.531)	2.808 (4.432)	2.633 (2.536)	0.573 (2.79)	-1.933 (5.003)	1.011 (4.83)
	Wealth	-4.808** (2.159)	-2.942 (2.066)	-1.061 (3.811)	-0.313 (3.684)			-4.909 (5.185)	-2.945 (4.978)
	Health	-2.466** (1.123)	-3.142*** (0.913)	4.592 (3.446)	3.074 (4.447)	2.427 (2.303)	-0.173 (2.113)	0.706 (4.371)	1.833 (4.104)
	Labor	-5.642*** (1.477)	-5.242*** (1.537)	-0.0277 (4.796)	-0.598 (5.163)	-0.777 (2.702)	-2.314 (2.543)	-3.626 (4.851)	-1.749 (4.648)
	Education	-1.401 (5.657)	-1.986 (4.071)	3.723 (5.919)	1.299 (4.994)	3.508 (5.042)	0.982 (3.871)		
	Control Variables	Hhcommunity			-5.447** (2.572)	-3.466* (1.996)			-5.377* (2.788)
Time				1.402 (1.571)	3.619* (2.022)			1.29 (1.523)	2.712 (1.898)
Region				2.792 (1.82)	2.733 (2.328)			2.169 (2.166)	0.0695 (2.731)
Demographic				-2.766 (1.855)	-1.829 (1.73)			-2.623 (1.766)	-1.954 (1.605)
Socioeconomic				-2.574* (1.467)	-6.399*** (1.518)			-2.889* (1.58)	-7.065*** (1.549)
Geognature				-2.487 (1.865)	-3.604 (2.433)			-2.441 (1.854)	-3.31 (2.06)
Variables Shock	Method					-0.0782 (3.926)	2.685 (4.963)	1.899 (4.36)	7.111 (5.139)
	dis_1					-4.874 (4.639)	-5.656 (5.414)	2.375 (5.985)	-1.622 (6.125)
	dis_2					-4.441 (4.366)	-5.557 (5.523)	2.591 (5.717)	-1.911 (5.651)
	dis_3					-8.380*** (2.631)	-5.06 (3.07)	0.0378 (5.733)	-2.227 (4.947)
Observations	161	161	161	161	161	161	161	161	
R-squared	0.242	0.24	0.328	0.323	0.255	0.242	0.338	0.339	
Adjusted R-squared	0.197	0.195	0.259	0.253	0.195	0.181	0.254	0.256	
F-test (outcome variables)	6.57 (0.0000)	9.11 (0.0000)	2.98 (0.009)	6.23 (0.0000)	3.72 (0.0028)	2.46 (0.0302)	2.29 (0.0417)	4.82 (0.0004)	
F-test(control variables)			2.57 (0.0348)	5.79 (0.0002)			2.56 (0.0358)	7.82 (0.0000)	
F-test (shock variables)					2.79 (0.0402)	0.84 (0.5114)	0.71 (0.5894)	1.66 (0.1804)	

Source: Authors' calculations. Notes: <sup>a</sup> Robust standard errors (clustered by studies) in parentheses  
 \*\*\* p<0.01, \*\* p<0.05, \* p<0.1; <sup>b</sup> The numbers in parentheses under each set of F-test result shows P-value (Prob>F) at 95 percent confidence interval

More intriguingly, the longer-term welfare measures that are sometime investigated—poverty indicators, wealth, health and labour market measures—do not yield unambiguous results in the breakdown regressions in Table 4. In the un-weighted regressions, wealth and labour market indicators are consistently negative, but these coefficients are statistically significant in model (1) only, so we are reluctant to attach much importance to these estimates.

Two variables appear to be consistently estimated to be statistically significant. These are the controls for household heterogeneity, and for socio-economic characteristics. This finding endorses a theme that is found in several research projects. They typically point to differential access to recovery funding and/or credit as a major determinant of the post-disaster economic dynamics (e.g., Sawada and Shimizutani, 2008, at the microeconomic level, and Noy, 2009, at the aggregate macro level). We can conclude here that disaster impacts are not ‘an equal opportunity menace’ and that disasters exact a differential impact on households with different characteristics belonging to different socio-economic strata. While we do not know the exact general pattern of differential impacts, prior evidence suggests that the poor are more adversely affected by disasters than groups from more privileged socio-economic backgrounds; especially when these affects are measured by poverty indicators or by health and labour outcomes (e.g. Noy and Patel, 2014; Hallegatte et al., 2017).<sup>11</sup>

Finally, when comparing the different columns in Table 4, we observe that the weighted models, and the ones that include controls for the community, time, region, demographic, socio-economic and geographical characteristics—models (2) and (4)—have a significantly higher fit (higher adjusted R<sup>2</sup>).

A separate research agenda, whose methodology did not allow us to include many of the projects within this stream in the corpus of papers we examine, focus on the role of social cohesion in the affected communities and the various types of social capital (bonding, linking, bridging) in determining post disaster recovery. Aldrich (2012) includes a thorough investigation of this literature and a summary of the evidence.<sup>12</sup>

For example, Aldrich and Sawada (2015) provide a recent investigation of the importance of social capital in determining mortality due to the tsunami wave generated by the Sendai earthquake of 2011. So, it might be the case that the variables we interpret as proxies for access to resources (credit or otherwise) are also correlated with the presence of social capital in the affected communities. Given our method, we are unable to differentiate between the two channels (nor do we think these are mutually exclusive interpretations of the evidence).

Human capital (education) and health outcomes also appear to be adversely affected by disasters. This result is, however, robust (statistically

<sup>11</sup> We thank Stephane Hallegatte for suggesting this interpretation of the evidence.

<sup>12</sup> Kage (2011), Klinenberg (2002) and Chamlee-Wright (2010) are all book-length investigations of the role of social capital in specific case-studies.

significant) for health outcomes in model (1) only, the model that does not include household and socio-economic controls. The decline in health and educational outcomes in models (3) and (4) could potentially explain the observed and relatively milder impacts on consumption; though the methodology does not allow us to precisely identify that.<sup>13</sup> The results on labor market indicators also portray the adverse (negative) impact of disasters particularly in models (2) and (4).<sup>14</sup>

However, the impacts on wages and labor force participation rates could not be differentiated due to less variation in the disaggregated data.

Again, the negative and statistically significant coefficients for household heterogeneity and the socio-economic characteristics support the hypothesis of differential impact of disasters. In this case, the coefficient for household heterogeneity in column 4 (OLS regression in model 4) indicates that if the estimated model does not control for household heterogeneity in the impacted households, this will mean that the estimated effect of disasters on income will be higher by 5.38 percentage points. That is, the impact on per capita income (*income\_2*) would have been larger than 8.5 percentage point if not controlled for household heterogeneity in our estimated model. We find no statistically consistently observable difference in estimation results for the poverty, wealth, and health, labor, and education indicators, and across the various methodological approaches adopted in this literature. Finally, the estimates regarding the disaster indicators mostly illustrates the comparison between hydro-meteorological events—primarily floods, rainfall and tropical cyclones—and geo-climatological ones. We find no robust evidence that different types of disasters have a differential impact.

## 5 Robustness Checks

As robustness checks, in Table 5, we split our sample to samples focused on consumption and non-consumption outcome measures, and conducted meta-regression analysis with our baseline model and these samples separately.<sup>15</sup>

We do not observe any systematic difference on poverty-disaster impact outcomes. The controls for household heterogeneity and socio-economic characteristics appear to be statistically significant in most cases as was the case previously.

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<sup>13</sup> 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).

<sup>14</sup> This result corresponds with the findings of Mueller and Osgood (2009a), Mueller and Quisumbing (2011), Mahajan (2012) and Shah and Steinberg (2012).

<sup>15</sup> This is due to having fewer observations in non-consumption outcome categories of interest.

**Table 5. Meta-regression Results with Restricted Observations**

Variables	Consumption		Non-consumption	
	OLS	WLS	OLS	WLS
CONSUME_1	-29.85** (11.85)	-40.16*** (10.51)		
CONSUME_2	-34.14** (12.25)	-48.18*** (11.20)		
INCOME_1				5.71 (4.18)
INCOME_2			-11.33** (4.48)	0.95 (4.15)
POVERTY			-5.27 (5.27)	9.31** (4.43)
WEALTH			-8.93** (3.62)	
HEALTH			-2.34 (3.20)	7.13* (3.91)
LABOR			-6.91 (4.37)	4.39 (4.53)
EDUCATION			-3.32 (4.89)	5.21 (5.78)
HHCOMMUNITY	23.14*** (6.63)	28.98*** (6.78)	-7.05** (2.75)	-5.44*** (1.64)
TIME	0.69 (3.70)	-1.05 (4.24)	0.53 (2.82)	0.44 (2.56)
REGION	-4.47 (3.17)	-7.77* (4.03)	3.35 (2.83)	2.36 (3.26)
DEMOGRAPHIC	-11.89** (4.84)	-15.27** (5.36)	-2.60 (2.00)	-3.36** (1.56)
SOCIOECONOMIC	-4.42 (3.66)	-4.48 (4.11)	-3.96** (1.73)	-8.63*** (1.49)
GEOGNATURE	0.94 (2.91)	1.11 (4.10)	-3.75 (2.88)	-5.35** (1.99)
METHOD	15.08* (7.67)	22.66*** (7.47)	7.35 (5.32)	13.09*** (3.66)
DIS_1	-0.71 (1.29)	-0.39 (1.46)	2.96 (5.10)	-8.22** (3.94)
DIS_2			2.18 (4.48)	-10.10** (4.15)
DIS_3	5.08 (5.50)	9.56** (4.46)	-3.32 (6.61)	-23.45*** (6.05)
OBSERVATIONS	52	52	109	109
R-SQUARED	0.32	0.36	0.44	0.43
ADJUSTED R-SQUARED	0.14	0.19	0.34	0.33

Source: Authors' calculations.

Note: Robust standard errors (clustered by studies) in parentheses \*\*\* p<0.01, \*\* p<0.05, p<0.1.

However, the coefficients for household characteristics are found positive and significant in consumption outcomes. This demonstrates



consumption smoothing through cutting non-food consumption (e.g. education and health) and spending more on food consumption in the aftermath of a natural disaster. The coefficients for household characteristics and socio-economic controls are negative and significant in non-consumption outcome measures suggesting their presence would further worsen the impact of disasters on this category.

## 6 Conclusions

Natural disasters affect households adversely, and they do so especially for people with focusing especially on the poor and on poverty measures. We find lower incomes and wealth that are less able to smooth their consumption. We conducted a meta-regression analysis of the existing literature on the impacts of disasters on households, much heterogeneity in these impacts, and this is most likely the most important insight gleaned from our analysis. There is no 'one-size fits all' description of the ways disasters have an impact on poverty, and the poor.

Yet, several general patterns that are observed in individual case studies also 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 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 under-development and poverty traps (World Bank, 2014).

The literature on the impact of disasters—both intensive and extensive—on the welfare of households, is growing daily. A remaining important 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 implies the possibility that disasters prevent long-term investment and therefore trap households in cycles of poorer education and health outcomes and persistent poverty.

The general pattern of post-shock dynamics is established with the meta-regression analysis we conducted here, and the need to develop the policy instruments that can deal with these dangers is clearer. One potentially promising tool for transferring this risk, and protecting households from the indirect impact of disasters is the provision of insurance. The distribution of insurance products, especially within the context of urban poverty in low-income countries, is facing significant challenges. This appears to be one potential tool that needs to be examined further.

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## Appendix. Standard of Dependent Variables

Following the data collection from the 38 papers included in our sample, we 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. The literature sometimes uses other methods to standardize the dependent variable; for example, by using t-statistics if the question that is being answered relates to the precision of estimates (e.g., Lazzaroni and van Bergeijk, 2014). Given the diverse nature of our dependent variables, we chose to standardize by calculating the percentage change in the examined indicator. We considered other methods that rely on indicator-specific second moments as less appropriate in this case.

In cases where seasonal impacts of disasters (e.g. rainfall) had been reported (e.g., Asiimwe and Mpuga, 2007), index values are used (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. For more discussion on the various potential measures of the dependent variable in meta-analysis, see Borenstein et al. (2009, chapter 4). Other recent papers that follow a similar standardization procedure in a meta-regression context are Rose and Dormady (2011) and Mazzotta et al. (2014). 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. The standardization also includes a sign change (+/-) with a positive sign implying a positive ('favorable' in a normative sense) impact on poverty and welfare outcomes due to natural disaster whereas a negative sign suggesting the opposite.



**Appendix Table 1. Descriptive Statistics of Variables Defined**

<b>Variables</b>	<b>Observations</b>	<b>Mean</b>	<b>Median</b>	<b>Std. Dev.</b>	<b>Min</b>	<b>Max</b>
Y	161	-2.01	-0.75	7.89	-32.23	24.96
N	161	28076.38	3823	69540.15	94	446780
INCOME	161	0.13	0	0.34	0	1
INCOME_1	161	0.07	0	0.25	0	1
INCOME_2	161	0.06	0	0.24	0	1
CONSUMPTION	161	0.32	0	0.47	0	1
CONSUME_1	161	0.24	0	0.43	0	1
CONSUME_2	161	0.08	0	0.27	0	1
POVERTY	161	0.12	0	0.33	0	1
WEALTH	161	0.06	0	0.23	0	1
HEALTH	161	0.18	0	0.39	0	1
LABOUR	161	0.12	0	0.33	0	1
EDUCATION	161	0.06	0	0.24	0	1
HH/COMMUNITY	161	0.80	1	0.40	0	1
TIME	161	0.67	1	0.47	0	1
REGION	161	0.76	1	0.43	0	1
DEMOGRAPHIC	161	0.37	0	0.48	0	1
SOCIOECONOMIC	161	0.62	1	0.49	0	1
GEOG/NATURE	161	0.54	1	0.50	0	1
METHOD	161	0.96	1	0.19	0	1
DISASTER	161	1.46	1	0.66	1	3
DIS_1	161	0.63	1	0.48	0	1
DIS_2	161	0.27	0	0.45	0	1
DIS_3	161	0.09	0	0.29	0	1

Source: Authors' calculations.

**Appendix Table 2. Meta-regression Results: The Direct and Indirect Impacts**

Variables	(1)		(2)		(3)		(4)	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
Income_1	5.531*** (1.643)	2.129 (4.460)	8.519** (3.215)	5.040 (3.621)	10.25*** (2.753)	-0.497 (6.271)	4.714 (4.451)	1.570 (5.193)
Income_2	-	-9.365***	-5.170	-2.945	-5.087	-	-8.548	-5.708
Consume_1	9.901*** (3.623)	0.193 (2.014)	5.779 (4.463)	4.996 (4.383)	6.829** (4.415)	-2.082 (5.278)	3.075 (5.833)	2.821 (5.150)
Consume_2	0.829 (1.615)	-5.848 (1.809)	5.163 (3.525)	2.341 (3.169)	2.713 (2.563)	-8.462 (5.005)	1.449 (4.462)	-1.521 (4.817)
Poverty	-2.106 (1.800)	-5.848 (4.170)	5.163 (4.111)	2.341 (4.771)	2.713 (2.802)	-8.462 (6.024)	1.449 (4.897)	-1.521 (5.671)
Wealth	-2.475 (1.662)	-2.241 (1.489)	1.424 (3.531)	2.808 (4.432)	2.633 (2.536)	-4.984 (5.931)	-1.933 (5.003)	-0.900 (5.660)
Health	-4.808** (2.159)	-2.942 (2.066)	-1.061 (3.811)	-0.313 (3.684)	-	-5.557 (5.523)	-4.909 (5.185)	-4.856 (5.248)
Labor	-2.466** (1.123)	-3.142*** (0.913)	4.592 (3.446)	3.074 (4.447)	2.427 (2.303)	-5.730 (5.136)	0.706 (4.371)	-0.0778 (5.052)
Education	-	-5.242***	-0.0277	-0.598	-0.777	-7.871	-3.626	-3.660
	5.642*** (1.477)	(1.537)	(4.796)	(5.163)	(2.702)	(5.486)	(4.851)	(5.395)
Hhcommunity	-1.401 (5.657)	-1.986 (4.071)	3.723 (5.919)	1.299 (4.994)	3.508 (5.042)	-4.575 (5.729)	-	-1.911 (5.651)
Time			-5.447** (2.572)	-3.466* (1.996)			-5.377* (2.788)	-4.182* (2.189)
Region			1.402 (1.571)	3.619* (2.022)			1.290 (1.523)	2.712 (1.898)
Demographic			2.792 (1.820)	2.733 (2.328)			2.169 (2.166)	0.0695 (2.731)
Socioeconomic			-2.766 (1.855)	-1.829 (1.730)			-2.623 (1.766)	-1.954 (1.605)
Geognature			-2.574* (1.467)	-	6.399*** (1.518)		-2.889* (1.580)	-
Method								7.065*** (1.549)
dis_1					-0.0782 (3.926)	2.685 (4.963)	1.899 (4.360)	7.111 (5.139)
dis_2					-4.874 (4.639)	-0.0985 (1.811)	2.375 (5.985)	0.289 (1.129)
dis_3					-4.441 (4.366)		2.591 (5.717)	
Observations					-	0.497	0.0378	-0.315
R <sup>2</sup>					8.380*** (2.631)	(5.071)	(5.733)	(4.963)
Adjusted R <sup>2</sup>	161	161	161	161	161	161	161	161
F-test	0.242	0.240	0.328	0.323	0.255	0.242	0.338	0.339
(outcome variables)	0.197	0.195	0.259	0.253	0.195	0.181	0.254	0.256
F-test(control variables)	6.57	9.11	2.98	6.23	3.72	2.34	2.29	4.29
F-test(shock variables)	(0.0000)	(0.0000)	(0.0090)	(0.0000)	(0.0028)	(0.0335)	(0.0417)	(0.0007)
			2.57 (0.0348)	5.79 (0.0002)			2.56 (0.0358)	7.82 (0.0000)
					2.79 (0.0402)	0.46 (0.7133)	0.71 (0.5894)	2.16 (0.1096)

Source: Authors' calculations.

 Notes: <sup>a</sup> Robust standard errors (clustered by studies) in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1; <sup>b</sup> The numbers in parentheses under each set of F-test result shows P-value (Prob>F) at 95 percent confidence interval.