POVERTY AND NATURAL DISASTERS: A META-REGRESSION ANALYSIS

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ABSTRACT:

We conduct a meta-regression analysis of the existing literature on the impacts of disasters on households. 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. 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 these services is often better viewed as long-term investment. We do not find consistent patterns in long-term impacts on health and education outcomes; 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 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 process of development and income growth. 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.[1]

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

[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.

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

For readers who are not familiar with this methodology, "meta-analysis is a body of statistical methods that have been found useful in reviewing and evaluating empirical research results. If a number of independent studies have been conducted on a particular subject, using different data sets and methods, then combining their results can furnish more insight and greater explanatory power than the mere listing of the individual results. In particular, meta-regression analysis is a form of meta-analysis especially designed to investigate empirical research in economics….the dependent variable is a summary statistic, perhaps a regression parameter, drawn from each study, while the independent variables may include characteristics of the method, design and data used in these studies. Thus, meta-regression analysis can identify the extent to which the particular choice of methods, design and data affect reported results." (Stanley, 2001, pp. 132-133).

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.[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 formally in meta-regression analysis. According to guidelines put forward 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 examples include Card and Krueger (1995), Smith and Huang (1995), Brander et al. (2006), and Disdier and Head (2008). We essentially provide an

[2] 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 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).

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.

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%) 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. 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. 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]

[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

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 order to prevent any publication bias we also included working papers and other unpublished work we found while following our search procedure described below.[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

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).

[5] 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.

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.[6] 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, 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.

[6] 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.

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 (grouped natural shocks). Table 2 provides additional information.

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. 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., van Bergeijk and Lazzaroni, 2013). 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.[7] 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.[8] The standardization also includes a sign change (+/-) with a positive sign implying a positive ('favourable' in a normative sense) impact on poverty and welfare outcomes due to natural disaster whereas a negative sign suggesting the opposite.

[7] 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).

[8] 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 gleaned from the 38 studies 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 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, labelled y_i, whose construction was detailed in the previous section. C_i is the vector of outcome variables that are potentially examined in each paper *i.* Details of the outcome variables and their coding are available in table 2. 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. μ_i representing the error term; we assume the error terms are clustered by study. α , β, and δ are the estimated coefficients of the respective explanatory variables included in our estimated regressions.

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.[9] We tested for multi-colinearity using and comparing various sub-sets of observation for further robustness checks.

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.[10]

4. Estimation results

Our meta-regression 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.[11]

We first examine the outcome variables in table 4. For income, for example, we mostly obtain a negative coefficient in most specifications (though rarely statistically significant). In

[9] 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.

[10] 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.

[11] See Willett and Singer (1988).

this case, a negative coefficient is interpreted to mean that when one examines the impact of disasters on income (rather than on another outcome measure), one observes a more negative impact; in short, disasters appear to decrease incomes more (in percentage terms) than other impact measures such as consumption. While the coefficient on income is mostly negative and the coefficient on consumption is generally positive, both are statistically different from zero (statistically significant) in some specifications, and not in others.

It is important to note, however, that the magnitudes of the coefficients are quite large, even if they are imprecisely estimated. The largest coefficient we estimate point to a decrease in income of 4.8 percentage points relative to consumption, and most other statistically significant estimates (see table 5) are even larger.

This finding of a 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.[12] More results about the types of income and consumption that are impacted are available in table 5. 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.

More intriguingly, the longer-term welfare measures that are sometime investigated—poverty indicators, wealth and labour market measures—all appear to be consistently negatively affected by disasters, as can be seen especially in table 4 column 4. We find that wealth tends to decrease due to a natural event, the poverty rates appear to increase and

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[12] 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.

health outcomes deteriorate. The evidence on human capital accumulation (education) is more ambiguous.

When comparing the different columns in table 4, we observe that the models that include controls for the community, time and demographic characteristics reduced the statistical significance of our results regarding the differential impact of disasters on different outcome variables. Though the inclusion of these controls does not always change the absolute value of the coefficients. This observation suggests that the pattern of impacts we described (with least impact on current consumption) is also dependent on the characteristics of the affected communities. This is a theme that emerges 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, and Noy, 2009). 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; especially when these affects are measured by poverty indicators or by health and labour outcomes.

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. We note that agricultural income (INCOME1) actually appears to increase, relative to other measures, in the post-disaster period.

Similarly for consumption, any relatively milder 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, relative to the mean, according to the evidence we have. Non-food consumption appears to increase more than other types of consumption measures. We note that this measure might be correlated with longer-term investments (in human and social capital in particular) so that this comparatively positive result is potentially positive.

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. There is no observable evidence that alternative measures of both education accumulation (EDUC1) and health status (HEALTH1) yield similarly adverse results. Thus, spending on health and education decreased quite dramatically in a post-disaster environment, but there is no evidence that outcomes, which should usually take years to manifest, have changed.[13]

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 decline as the result of a disaster.[14] There seem to be no identifiable impact on labor force participation rates, relative to the mean. As before, we still observe negative and statistically significant coefficients for the socio-economic controls.

In contrast with the fairly coherent and consistent evidence regarding incomes, consumption, labour, health and education outcomes, the evidence on the impact of disasters on poverty or wealth indicators is not as easy to interpret. We find that for both poverty

[13] 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).
[14] 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).

indices and wealth indicators, the coefficients we identify are not statistically different from zero. We conclude that on average disasters do not impose disproportionate adverse impacts along these dimensions.

We use six control indicators in our estimation model to account for the variables the investigated studies measure in their estimations. Evidence from our estimation results, depicted in both table 4 and 5, suggests that accounting for household heterogeneity is important in identifying disaster outcomes, but does not really change our main conclusions described above. We do observe that the coefficients on the socio-economic and demographic variables of affected households and communities are statistically different from the null, indicating the importance of these variables when estimating the impact of disasters. These coefficients are consistently negative, suggesting that once we account for these socio-economic and demographic controls, the estimated adverse impact of a disaster (on incomes, consumption, wealth, etc.) is worse.

We find no statistically observable difference in estimation results across the various methodological approaches adopted in this literature. Finally, the estimates regarding the disaster indicators mostly illustrates the comparison between the hydro-meteorological events primarily floods, rainfall and tropical cyclones and the geo-climatological events. We do not find any evidence that different types of disasters have a differential impact on our outcome variables.

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 sub-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). We compare results for the model that utilize all LHS observations (161 observations), a model that includes all the LHS>0 observations (70 observations) and finally, a model that only includes the LHS<0 observations (91 observations).

The estimations based upon the sub-samples 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. We observe several other patterns, but these results do not seem to be very robust statistically. Results are available upon request.

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 that often 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 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. 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 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 (such as index insurance) especially within the context of urban 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**
OUTCOME VARIABLES	**INCOME**	-2.503	2.042	-2.753	-1.790	1.856	0.995	-1.818	-4.761
		(5.417)	(4.051)	(5.504)	(4.522)	(4.972)	(4.120)	(4.704)	(4.100)
	CONSUMPTION	2.365	6.934*	-0.193	1.799	6.081	5.451*	0.0956	-0.999
		(4.372)	(4.046)	(4.201)	(3.510)	(3.750)	(2.972)	(1.448)	(2.262)
	POVERTY	-1.677	4.437	-3.378	0.181	2.651	3.955	-2.475	-2.241
		(5.158)	(4.835)	(4.638)	(2.958)	(4.188)	(4.555)	(1.651)	(1.479)
	WEALTH	-5.398		-5.704		-0.632	0.165	-4.808**	-2.942
		(5.180)		(4.743)		(4.152)	(3.885)	(2.145)	(2.053)
	HEALTH	0.711	5.518	-3.112	-0.00269	5.251	4.409	-2.466**	-3.142***
		(4.329)	(3.899)	(4.404)	(2.098)	(3.837)	(4.411)	(1.116)	(0.907)
	LABOR	-3.459	1.660	-6.368	-2.407	0.725	0.589	-5.642***	-5.242***
		(4.811)	(4.570)	(4.784)	(2.618)	(5.171)	(5.152)	(1.468)	(1.527)
	EDUCATION		3.270	-1.998	1.150	4.313	2.267	-1.401	-1.986
			(5.122)	(6.751)	(3.786)	(6.116)	(4.791)	(5.620)	(4.045)
CONTROL VARIABLES	**HHCOMMUNITY**	-5.115*	-4.392**			-4.936*	-3.899**		
		(2.998)	(2.062)			(2.732)	(1.767)		
	TIME	0.0902	2.371			0.409	3.024		
		(1.609)	(1.750)			(1.691)	(1.950)		
	REGION	2.839	1.732			3.612*	3.796		
		(2.261)	(2.661)			(2.034)	(2.486)		
	DEMOGRAPHIC	-2.668	-2.362			-2.731	-2.151		
		(1.893)	(1.496)			(1.960)	(1.560)		

	SOCIOECONOMIC	-4.402***	-8.062***			-3.921**	-7.327***		
		(1.503)	(1.352)			(1.460)	(1.475)		
	GEOGNATURE	-2.616	-4.012*			-2.662	-4.180		
		(1.900)	(2.180)			(1.956)	(2.670)		
SHOCK VARIABLES	**METHOD_1**	4.779	6.880	1.752	2.533				
		(4.949)	(5.203)	(4.387)	(5.057)				
	DIS_1	0.658	-4.553	-1.283	-5.686				
		(6.294)	(5.427)	(1.575)	(5.506)				
	DIS_2	1.467	-4.366		-4.949				
		(6.039)	(5.466)		(5.680)				
	DIS_3	-0.499	-4.267	-2.712	-3.460				
		(5.997)	(3.528)	(4.577)	(3.529)				
	OBSERVATIONS	161	161	161	161	161	161	161	161
	R^2-ADJUSTED	0.1863	0.2351	0.0705	0.1069	0.1838	0.2345	0.0760	0.1208
	F-TEST (OUTCOME VARIABLES)	2.06 (0.0818)	4.21 (0.0025)	1.71 (0.1377)	0.82 (0.5648)	2.64 0.0256)	5.83 (0.0001)	4.14 (0.0019)	7.60 (0.0000)
	F-TEST(CONTROL VARIABLES)	4.07 (0.0031)	11.79 (0.0000)			3.26 (0.0112)	6.65 (0.0001)		
	F-TEST (SHOCK VARIABLES)	1.47 (0.2312)	1.85 (0.1392)	0.87 (0.4666)	0.61 (0.6552)				

Source: Authors' Calculations

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

The numbers in parentheses under each set of F-test result shows P-value (Prob>F) at 95% confidence interval.

TABLE 5: META-REGRESSION RESULTS B: THE DIRECT AND INDIRECT IMPACTS

		(1)		(2)		(3)		(4)	
	VARIABLES	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
OUTCOME VARIABLES	INCOME_1	10.95	-3.649	13.48	3.142***	8.092**	7.479***	5.820***	5.820***
		(10.60)	(3.760)	(11.20)	(0.837)	(3.013)	(2.401)	(0)	(0)
	INCOME_2	11.00	-6.560	13.00	-2.170	8.058**	4.080	5.290*	0.238
		(9.806)	(4.579)	(10.11)	(5.315)	(3.656)	(4.244)	(3.003)	(5.400)
	INCOME_3	-2.911	-14.43***	-2.108	-11.65***	-6.156	-4.192	-9.901**	-9.365***
		(11.64)	(2.846)	(11.74)	(2.178)	(3.873)	(3.195)	(3.684)	(2.048)
	CONSUME_1	9.011	-5.412	9.805	-1.908	5.206	4.778**	0.829	0.193
		(10.67)	(3.907)	(10.97)	(2.402)	(3.129)	(2.104)	(1.642)	(1.840)
	CONSUME_2	4.679	-12.55**	3.591	-10.61**	1.626	-1.812	-4.194*	-8.221**
		(10.49)	(5.146)	(10.58)	(4.188)	(3.985)	(4.430)	(2.288)	(3.974)
	CONSUME_3	13.37		10.42		10.34***	11.18***	2.593***	2.418***
		(11.38)		(11.31)		(3.547)	(3.248)	(0.641)	(0.614)
	POVERTY	4.819	-6.038	5.606	-4.923**	1.507	4.662	-2.475	-2.241
		(11.74)	(4.231)	(11.29)	(2.001)	(3.486)	(4.333)	(1.690)	(1.514)
	WEALTH	1.479	-11.20***	2.977	-5.347**	-1.597	-0.305	-4.808**	-2.942
		(11.16)	(3.670)	(11.49)	(2.241)	(3.645)	(3.230)	(2.195)	(2.101)
	HEALTH_1	8.574	-4.193*	5.811	-2.714**	5.494*	6.122*	-2.061*	-0.539
		(11.29)	(2.089)	(11.57)	(1.031)	(3.225)	(3.163)	(1.105)	(0.484)
	HEALTH_2		-26.30***		-24.14***	-3.411	-16.12***	-7.940	-21.98***
			(2.526)		(1.606)	(10.88)	(3.287)	(11.24)	(1.443)
	EDUC_1	9.450	-0.677	8.754	-0.502	6.285	9.719**	0.866	1.678
		(12.21)	(3.629)	(12.76)	(1.996)	(5.888)	(4.403)	(5.778)	(1.842)
	EDUC_2	-13.20	-26.09***	-13.86	-23.96***	-16.56***	-15.91***	-21.80	-21.80***
		(11.52)	(2.175)	(11.36)	(0.879)	(3.866)	(3.565)	(0)	(0)
	LABOR_1	2.115	-9.950**	1.390	-9.460***	-1.043	0.626	-6.418***	-6.778***

		(12.44)	(3.714)	(12.09)	(1.853)	(4.690)	(4.836)	(2.231)	(1.604)
	LABOR_2	6.913	-2.808	4.107	-3.564	3.655	7.476	-3.833	-1.408
		(12.81)	(4.758)	(12.26)	(2.984)	(6.638)	(5.646)	(4.569)	(2.713)
CONTROL VARIABLES	**HHCOMMUNITY**	-5.563**	-4.588**			-5.762**	-4.735***		
		(2.521)	(1.880)			(2.333)	(1.543)		
	TIME	1.482	2.353			1.526	2.567		
		(1.514)	(1.477)			(1.588)	(1.602)		
	REGION	3.227	2.072			3.490*	3.076		
		(2.142)	(2.400)			(1.809)	(1.939)		
	DEMOGRAPHIC	-4.216**	-6.597***			-4.257**	-6.320***		
		(1.714)	(1.860)			(1.737)	(1.626)		
	SOCIOECONOMIC	-1.705	-3.816**			-1.541	-3.292*		
		(1.557)	(1.629)			(1.468)	(1.669)		
	GEOGNATURE	-2.809	-3.098			-2.956	-3.504		
		(2.173)	(2.343)			(2.179)	(2.674)		
SHOCK VARIABLES	**METHOD_1**	0.643	4.020	-0.0727	2.732				
		(3.931)	(4.518)	(3.997)	(5.037)				
	DIS_1	-3.878	7.352	-7.867	-0.575				
		(11.62)	(4.666)	(12.01)	(5.131)				
	DIS_2	-3.142	8.374*	-7.403	0.294				
		(11.37)	(4.484)	(11.70)	(5.126)				
	DIS_3	-5.693	8.329**	-11.36	0.314				
		(11.03)	(4.077)	(10.99)	(2.396)				
	OBSERVATIONS	161	161	161	161	161	161	161	161

	R^2-ADJUSTED	0.3163	0.5139	0.2395	0.4559	0.3235	0.5174	0.2400	0.4625
	F-TEST (OUTCOME VARIABLES)	59.64 (0.0000)	306.19 (0.0000)	311.46 (0.0000)	347.63 (0.0000)	111.98 (0.0000)	365.87 (0.0000)	4.78 (0.0001)	47.83 (0.0000)
	F-TEST(CONTROL VARIABLES)	3.82 (0.0046)	6.23 (0.0001)			3.76 (0.0050)	6.42 (0.0001)		
	F-TEST (SHOCK VARIABLES)	0.53 (0.7170)	4.97 (0.0026)	2.02 (0.1123)	3.12 (0.0261)				

Source: Authors' Calculations

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

The numbers in parentheses under each set of F-test result shows P-value (Prob>F) at 95% confidence interval.

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