Assessing the Relationship between Natural Hazards and Poverty

A Conceptual and Methodological Proposal

Regional Programme on Capacity Building for Sustainable Recovery and Risk Reduction

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Motivation and Objectives

1.1 Policy and development context

The International Strategy for Disaster Reduction (ISDR) secretariat and the World Bank with the United Nations Development Programme (UNDP) and other partners are currently coordinating the preparation of the ISDR system's first biennial *Global Assessment Report on Disaster Risk Reduction* (GAR) (ISDR, 2009).

The GAR will fulfill three main objectives:

- It is expected that the report will establish itself as a credible and widely accepted reference point for information on global hazard patterns and trends.

- It will strengthen the ISDR system's capacity for planning and joint programming at all levels by providing a global review of achievements and gaps in hazard risk reduction from national, regional and thematic reporting.

- Each issue of the GAR will increase understanding and awareness of the mutually supportive relationship between development and hazard risk reduction, through an in-depth analysis of key linkages and interfaces between hazards and a development theme of global concern.

Related to the third point, a series of major developments at both the international and national level have reasserted the need to understand and reduce poor people's exposure to external and largely uncontrollable climatic or geological hazards that reinforce the poor's sense of ill-being and exacerbate their material poverty.

The findings from worldwide consultations with the poor carried out by the World Bank in preparation for its report on *Attacking Poverty* (World Bank, 2000), UNDP's recognition of the mutual links between disasters and development (UNDP, 2004) and the UK Department for International Development's explication of the links between development and disasters in view of the long-term impacts on poverty trends (DFID, 2004), have helped to prioritize policy attention on the links between poverty and disaster risk over the past years.

Significant social and economic consequences of major recent natural hazards in different parts of the world have reiterated the need to place hazard concerns higher on the global poverty agenda. In parallel, the mounting evidence that global climate change is catapulting the recurrence and virulence of climatic hazards in vast parts of the world, such as droughts and floods, has reinforced the sense of urgency to address this matter.

In view of these significant developments over past years and the lack of empirical research on the issue, consultations with the International Federation of Red Cross and Red Crescent Societies, ProVention Consortium, UN Children's Fund, UNDP, UN Environment Programme (UNEP), World Bank, and various non-governmental organizations, have concluded that the 2009 GAR should analyse the relationship between natural hazards and poverty through quantitative and qualitative approaches.

The evidence presented will make the case for hazard risk reduction as a key instrument to reduce poverty and for poverty reduction strategies in turn, to contribute to reducing people's susceptibility[1] to hazard events.

1.2 Methodological considerations

The growing concern with the foreseeable effect of geological and climatic hazards on poverty has not yet translated into a coherent and systematic empirical research agenda that illustrates their connection, thus paving the way for policy-oriented action. Major reviews investigating poverty dynamics have noticed the scant evidence in this respect mainly due to the absence of hazard information in standard household surveys (Baulch and Hoddinott, 2000; Yaqub, 2000b; Dercon and Shapiro, 2007). This situation has started to change recently with the design of hazard modules in household surveys (including questions on natural hazards), some of which are still waiting to be transformed into longitudinal studies. A series of large-scale composite risk Atlas preparations in many parts of Asia has also initiated a process of national, regional and subregional risk assessments that could be linked to poverty (BMTPC, 1997, 2008; Beijing Normal University, 2004; TARU, 2005, 2008).

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1   This proposal employs the concept of susceptibility rather than vulnerability for two reasons. First, vulnerability might lead to confusion as practitioners from different disciplines use different meanings and concepts of vulnerability, which, in turn, have led to diverse methods of measurement and frameworks to understand it (Alwang et al., 2001). And second, within economics there seems to be an increasing agreement that should remain a forward-looking concept associated to a negative welfare outcome (Hoddinott and Quisumbing, 2003). This brings practical difficulties to map the effect of hazards on poverty given the data sources available in the GAR countries (see Annex I).

Where previous work on exploring the link between poverty reduction and hazard risk reduction exists, it has mainly focused on assessing poverty outcomes of large-scale catastrophic hazards. While these events have extreme impacts on poor populations, their infrequence makes it very difficult to establish a relationship with poverty trends over time, except at the macrolevel. In contrast, there is a large number of frequently occurring but highly localized events, such as fires, flash floods, landslides and storms that may represent a significant and unreported source of livelihood loss and disruption for marginal rural and urban populations, and thus, have a crucial interactive relationship with poverty patterns and trends. Therefore, it is also necessary to focus attention on the impacts of highly localized, low intensity hazards on poverty.

At the same time, some livelihood practices, especially under dire circumstances, are conducive to increased exposure to hazard loss or damage (Holloway, 2007). For instance, immigrants of poor households seeking to escape poverty in rural areas often arrive into or form urban squatter settlements, where land values are lowest and where the pressing need to acquire housing and basic services translate into substandard urbanization, characterized by unsafe dwellings, precarious or non-existent public infrastructure, and overcrowding. Altogether these factors create the breeding ground for a hazard (say a storm) to bring a disproportionate impact on such informal settlement residents. But while qualitative narratives abound in this respect, there is a lack of survey-based evidence to support the poverty-hazard nexus (Alwang et al., 2001).

Given the above reasons, this methodological proposal provides a selective overview of quantitative methods and tools that could be employed to assess the two way relationship between poverty and natural hazards (see Annex I for the working definitions).

As entry point for such purpose the following question are posed:

- Do natural hazards contribute or exacerbate poverty? This first overarching question can be tackled from various angles depending on the interest of research –

  – The time dimension ascribed to the effect on welfare (short-run or medium-run);

  – The scale of the hazard in question (extensive or covariate); and

  – The component(s) (consumption, health, nutrition) and metric of wealth (levels, trends or states over time) that are being analysed.

Further key questions to explore regardless of which mix of aspects drives research are the following:

- What economic sector or types of occupations will be affected by hazard impacts?

- What sorts of households are affected by hazard events?

- What makes some households protect their consumption on items such as education and health better than others during difficult times?

- Are the impacts of hazards on poverty levels gender specific/sensitive?

This proposal is also organized around the effect that poverty might have on the exposure of households to hazard loss. Therefore, a second group of questions that the methods proposed will try to address are the following:

- Can poverty in turn reproduce or exacerbate the loss or damage when hazards strike?

- Does poverty impact the susceptibility to loss of life, buildings and agricultural assets?

1.3 Outline of methodological proposal

The paper is organized in three sections to tackle the above research questions:

- Section 2 introduces the main working hypothesis underlying this proposal.

- Section 3 presents the theoretical framework suggested for exploring the two-way relationship between natural hazards and poverty.

- Section 4 introduces the measures and (statistical and econometric) techniques proposed to test the aforementioned hypothesis. The list of methods proposed will not be exhaustive. Only those methods considered relevant for the sources of data at hand within the selected country case studies for the GAR report will be examined.

Presentation in section 4 will follow the steps involved in any standard poverty study, namely:

- Identification of poverty that requires defining and measuring a welfare indicator to signal poverty;

- The experience of poverty that explores its incidence, depth and severity; and

- The explanations of poverty that ideally entails generating statements about its causes and not only reporting its correlates.

A few empirical examples and potential applications will be provided throughout the last section for illustrative purposes. Any explanation of results is guarded against as this is not a review of empirical findings. It should also be noted that econometric jargon and notation is kept to a

minimum to appeal to a wider audience. Finally, being a quantitative proposal, there will be an orientation towards the final welfare outcome to be able to quantify the impact of hazards on poverty. This will come at the expense of missing explanatory power over the interactions that take place between natural hazards and responses to them that eventually lead to such a final result. Therefore, prospects of cross-disciplinary collaboration with qualitative work are still necessary and desirable.

Two key hypotheses are proposed to tackle the central lines of research.

Hypothesis 1

Poverty is likely to correlate with (a) the exposure of households to natural hazards, and (b) their susceptibility to suffer loss from hazard events.

Part (a) stems from location factors as both rural and urban households are typically being pushed due to land ownership and market factors to marginal hazard prone areas (i.e., steep land or squatter settlements). Part (b) refers to housing materials of poorer quality, infrastructure, and production activities that are typically unsafe or less resilient to hazard impacts.

Hypothesis 2

Natural hazards are likely to (a) contribute to poverty by affecting human development indicators and assets directly, as well as indirectly through affecting their attributes of value and productivity; and (b) exacerbate the household's inability to avoid or recover from poverty due to their aggregate nature, in combination with the absence or inadequate application of coping mechanisms.[2]

Part (a) relates to the more visible impact of hazards on household members and assets themselves. Physical assets can be used for income-generating activities to entitle households to goods and services that facilitate achievement of different dimensions of well-being, such as consumption. Their depletion in turn, can lead to short-term welfare fluctuations and push people into sudden poverty. Human capital assets (i.e., nutrition and health), which can also improve people's ability to take advantage of income-generating opportunities, are important in their own right. Any effect on the bodies of household members (death, sickness, injury), therefore, can also lead to poverty.

Part (b) alludes to the fact that natural hazards are often highly covariate rendering co-insurance mechanisms less effective, which combined with lower physical and human capital endowments characteristic of poor households, make them badly situated to handle risk-related losses. It also suggests that existing policy responses and conditions at a more aggregate level (district and subdistrict level) may condition the extent to which households can avoid falling into poverty. Inadequate safety nets, unsound growth conditions alongside restricted access to credit and insurance markets, and uneven distribution patterns may lead to a less conducive environment for coping. This effect on poverty could also be appreciated where the district and subdistrict are the units of analysis.

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2   To be able to test the proposed hypothesis in empirical work, it was decided to categorize the impact of hazards on poverty as being the direct result from the hazard, or a ramification of its impact on their value or productivity due to their aggregate nature and the absence or inadequate application of coping mechanisms, both at the household and district levels. More conventional typologies could have been *ex ante* and *ex post* impacts relative to the hazard occurrence; or short, medium and long-term impacts relative to the welfare indicator (de la Fuente, 2007).

Conceptual Framework

The proposed framework to appraise the two way relationship between natural hazards and poverty has its building block in assets, first, because it makes sense to focus on the things that poor people have, rather than start from what they do not have (i.e., a certain amount of income). And second, because from the perspective of poor people, assets play a central role in determining the extent and ways in which they feel or become vulnerable to natural hazards and poverty (Narayan, et al., 2002; Vatsa and Krimgold, 2000).

3.1 Access to and ownership of assets

Households are the starting point of analysis and have tangible and intangible assets at their disposal (see Annex II section 2.2).[3] While this focus can be kept for looking at the effect of natural disasters on poverty, it can also make sense to scale it up as asset responses to hazards are often affected by the broader policy context. Moreover, the predisposition of households to hazard loss can and has been traditionally scaled up to higher levels of aggregation (UNDP, 2004). It is the number of people located in certain areas combined with the human, material and environmental circumstances of households, and the localities where they live that shapes their collective possibilities to deal with a natural hazard. Therefore, the regional or district level of analysis was referred to while considering the implications that low asset endowments and their poor management can have for the susceptibility to experience larger hazard impacts, as well as for the implications that hazards can have on poverty.

But households and communities do not only rely on the asset endowments of varying size and composition they have *ad infinitum*. They also care about the processes conducive to their accumulation or improvement, which are asset-specific. These processes depend, among other things, on the rate of utilization of the asset itself, as well as the availability of and exchangeability with other assets, and on whether the household experiences any hazards or not. Empirically, the authors were less interested in describing the accumulation of each asset than observing its actual level at household and community levels.

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3 Household is understood here as a group of people living in the same dwelling, whether linked by kinship or not, who share living expenses and prepare food in the same kitchen.

3.2 Asset transformation

People manage and transform their asset stock into income and other outputs while pursuing a living (i.e., land is employed for obtaining staples or income rent from commodity sales). This could happen in a variety of ways. The main channel would be through their return as a consequence of getting involved in income-generating activities or letting other people use them (i.e., renting land) and thus earn a return from this. In addition, households can either invest or enhance the benefits derived from the possession of assets by selling, renting, loaning or exchanging them; or can try to substitute one asset for another (i.e., substitute remittances from a migrant household member for his or her direct labour); or combine one or more of these strategies (Bebbington, 1999; Rakodi, 1999).

Accessing, defending, transforming and mobilizing assets can happen at normal times or during extraordinary situations, such as the aftermath of a natural hazard. An adequate regulatory environment for housing in urban contexts or land titling in rural areas; state provision of socio-economic infrastructure, as well as public services to the population; and a sound economic environment for employment opportunities, can all facilitate the deployment and accumulation of assets during normal times. They improve household preparations against natural hazards (including a major accessibility for emergency services).

In times of contingency, the transformation of assets would be subject to various *ex ante* conditions, including institutional capacities at different government levels, available technologies, exogenous prices, infrastructure, and various other resources and market constraints, along with the type of hazard experienced (i.e., slow onset events: droughts versus rapid onset events: hurricanes or tsunamis). The reliance on informal strategies undertaken at the household and community level, such as asset-based self-insurance and group risk-sharing mechanisms is often insufficient to deal with natural hazards. Consumption smoothing is often not achieved through these private means due to numerous constraints, including the riskiness of assets and the covariance of natural hazards. For instance, guaranteed livestock purchases would avoid the problem that comes when the terms of trade between goods for consumption and assets change as a result of a common shock. Otherwise, if a negative shock occurs and everyone

tries to sell assets at the same time, asset prices will collapse and the amount of consumption that can be purchased with the proceeds will fall. Moreover, households can end up resorting to non-optimal coping strategies, such as cutting back food consumption below adequate levels. Altogether this evidence calls for the extensive and accessible involvement of government and other instances to support households and their communities (de la Fuente, 2007a).

Governments tend to embark in multiple *ex ante* and *ex post* strategies to deal with natural hazards. In the past, they have traditionally responded through in-kind disaster relief, but more recently there has been a tendency to emphasize cash transfers as well. Even if both measures are adopted, further effectiveness could be accomplished by adopting hazards reduction and mitigation mechanisms that address the structural factors that make households more exposed to natural hazards. Having mechanisms in place before the realization of hazards is fundamental. At the macrolevel, early warning systems and social funds that can involve community-based initiatives seem particularly relevant, so do subsidies, debt or revenue recovery write-off, as well as tax incentives for households or communities to adopt mitigation measures. Another form of defending the value of assets at the macrolevel could be through economic diversification. The increase in sectoral and spatial activities in the economy, resulting from the spread of input and output markets can provide a wider pool to spread the risk of suffering hazard losses, and additional opportunities to increase and stabilize returns. Conversely, the concentration of economic and sectoral activities would be consistent with reduced ability of households to manage and respond to hazards.

At the microlevel, providing households with safer assets, especially savings, and avoiding physical asset-based risk management strategies by focusing on the provision of credit for productive purposes and insurance products, are the best solutions devised. The provision of effective insurance mechanisms against the impacts of natural hazards, including employment guarantee schemes as a form of insurance or weather-based insurance would ideally be tied to removing behaviours that could reinforce the underlying conditions of precariousness and exposure to hazards.

There is also a set of intangible features that might potentially limit (improve) the household efforts to surmount the effect of natural hazards on them, just as unfavourable socio-economic opportunities might well do. The political economy and institutional features of the context where assets are deployed, along with the system of convictions, norms and beliefs embedded in the behaviour of communities' members might prove fundamental while employing and mobilizing assets for confronting hazards. Ideally, one should be able to explain how culture and governance arrangements come into play when they interact with the broader setting of hazards, assets and welfare outcomes. However, most of these features will be hard to operationalize empirically during a technical survey analysis. The analysis for this study is limited to acknowledging the potential for rich cross-fertilization between the proposed methods in this document and qualitative work in this respect. From this integrated thinking it might become more evident as to how and why these intangible features need to be incorporated into the analysis of the poverty-hazards equation.

3.3 Entitlements into welfare outcomes

All the above transformations of asset holdings can have a positive impact on welfare in three different ways. First, individuals extract higher utility revealed through consumption from owning higher asset levels. The second effect is that in theory higher asset levels can increase the income-generating potential of poor households leading to a reduction in poverty during normal times. This is so because income can entitle households to obtain consumption, nutrition, health and other dimensions of well-being, which in turn have a feedback effect on the asset base of households. And the last, and very important effect for welfare, is that asset holdings can buffer income fluctuations and thus improve poor people's ability in dealing with adverse hazards. Conversely, a reduced endowment and hostile circumstances to transform it will only exacerbate the poverty conditions of the household and its exposure to further hazards. The role played by the consumption smoothing property of assets depends on the importance of the hazards, and the level of development of the different asset-specific markets (i.e., credit and insurance) and state-funded mechanisms (safety nets). In practice, asset-based smoothing analysis will be difficult without multi-period panel datasets.

3.4 Hazard effects on poverty

The transformation of assets into welfare described above is not deterministic and unidirectional. This process can experience sudden disruptions and reversals through the various impacts of natural hazards. The physical contact of natural hazards with humans and/or with property can bring death, injury, disruption of socio-economic activities and damage or destruction to property and natural resources and other physical assets. In urban areas, livelihood outcomes of hazards are principally reflected in damage to housing, which in many contexts, constitutes a source of livelihood and not just welfare. Other outcomes may be reflected in the loss of infrastructure in which the poor have invested (water, sanitation, electricity) or in welfare facilities (schools, health centres). Drastically, an outcome may be the loss of land *per se:* for example, when a squatter settlement is destroyed by

a major mud-slide and it is impossible to rebuild on site. In rural areas, livelihood outcomes of natural hazards may be the loss of crops and livestock due to drought and flood with a consequent reduction in income and food intake, loss of income due to interruption of transport or access, and/or destruction of housing and infrastructure in urban areas. Since some of the above assets can be transformed into income-enhancing productive activities, their depletion can lead to short-term welfare fluctuations and push people into sudden poverty.

Arguably, the above effects can be explained regardless of the hazard scope and the coping capacity of each household. But these two factors can also conspire against the capacity of households to lift from or stay out of poverty after a natural hazard. This could be observed at the household and district level. When households have restricted means to protect the most vulnerable members inside them, such as the aged or children under 3, hazards can affect them through nutrition shortfalls. For the latter group, this in turn could have an impact on their human development later in life.

Sometimes, even when adequate mechanisms to mitigate and cope with hazards are in place, their application might not impede falling into poverty if the covariate nature of the problem is not well understood. The value of assets could drop if all affected households try to sell them at once or if the loss came over a key irreparable asset of the household, such as the death of the head. It is hard to assert in advance that asset prices will depress if households sell off all at once to face a sudden shock, but it is not unlikely for villages to experience the presence of high covariance between income and asset prices when aggregate shocks hit (Dercon, 2001).

Similarly, the presence of droughts and floods can be a deterrent to labour mobilization as they extensively affect the land, limiting the working opportunities of people around it. Likewise, being members of a rural financial institution where the majority of deposits are from community members engaged in agricultural activities may be of little help for lending purposes at the time of a natural hazard because most probably those deposits will be withdrawn to face any resulting flood or harvest failure (Skoufias, 2003).

On the other hand, the inability of households to maintain, or mobilize their meagre asset bases in the presence of natural hazards (which may condition the extent to which they can avoid falling into poverty) will also be shaped by 'transforming structures and processes' such as – governance and institutional arrangements, broader policies and existing conditions at subdistrict and district level, private sector activities, international agencies, civil society organizations, and socio-cultural influences.

Successful coping against hazards is harder to attain in a context of low productivity, staled economic growth, lack of access to productive assets (such as water, credit, etc.), absence of reserves and safety nets in place, and wide inequalities across geographic, racial, religious or ethnic lines. Lack of health facilities, remoteness and low levels of education may also compound these vulnerabilities. As a result, the covariate nature of many natural hazards and the policy-induced macro conditions affecting the speed and chances of successfully coping with them might reflect varying welfare impacts across district and subdistrict levels.

3.5 A dynamic reconfiguration: Poverty effects on the propensity to suffer hazard losses

The above framework intends to be dynamic, recognizing changes over time due to both external fluctuations and the results of household's own actions. This means that endowments are allocated to different activities in many ways, and then households might experience hazards and engage in various income and consumption-smoothing behaviours, which may determine how well households deal with them and preserve their endowment. In other words, households have to make decisions over time with regard to access and maintenance of assets, their transformation into income and its implications for the living conditions of households.

For (poor) households constrained by their assets and the conditions they face to transform them into valuable instruments to achieve well-being, this constant rearrangement of strategies and conditions can also render them more likely to bear the brunt of natural disasters (i.e., more likely to suffer damages from natural hazards) (World Bank, 2000).

This is true in the following senses: First, settling in places that can aggravate the exposure to hazards, such as living in hazard prone areas, where they usually can only afford to live in as a result of the narrow prospects faced. For instance, most major cities in developing countries have a significant proportion of their population living in squatter settlements or similar, and these often occupy hazard prone areas where land values are lowest. Many case studies have shown that households may accept increased hazard exposure in order to achieve an urban location that provides access to employment and services (Lavell, 1994). In rural contexts, poverty would also seem to be a key factor in explaining the increased likelihood to suffer hazard damages: Often the poor are located on marginal land, with greatest exposure to drought and flood or in areas where access and commerce is also exposed to interruption by floods and landslides (this point also applies to urban areas).

Figure 1: Assets, natural disasters and poverty: Suggested causalities
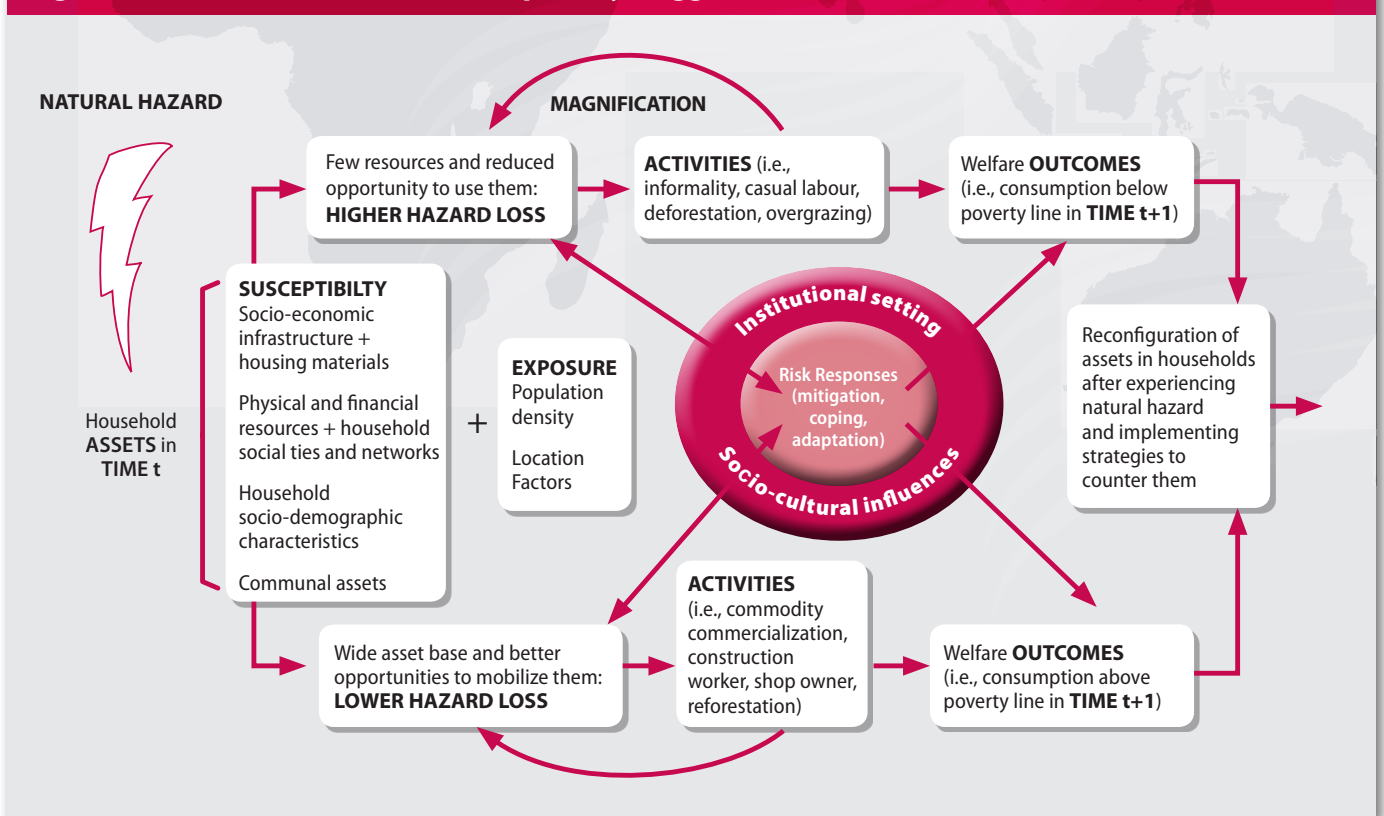
Second, poverty during normal times or in response to critical situations can lead to undesirable livelihood practices that magnify hazard levels or generate new hazards. In urban areas, this could happen through the destruction of vegetation cover on hillsides; the obstruction of water courses and drainage by housing constructions and through garbage disposal; drainage of wetlands, and so on. While this second order processes are not to be explored in the country analysis, some of them may be captured through Geographic Information System (GIS) techniques or community-level questionnaires to further inform the analysis of exposure to hazards.

Likewise, for rural areas, the over-exploitation of available resources in the form of overgrazing, deforestation, and excessive extraction of groundwater that result from overcrowding and persistent conditions of poverty are often cited in the literature as means through which hazard levels are increased (Blaikie et al., 1994).[4] This could happen as a short or medium-term coping strategy for communal land, despite being a highly valuable asset for its capacity to provide food and shelter, and sometimes for its income-generating potential. The population pressures on land

through a disproportionate exploitation of forest woods, coupled with over harvesting, and slash and burn agriculture, can lead to soil erosion. This can affect soil fertility and quality, making it not uncommon to find dry spells and droughts in the midst of acute environmental degradation, thus undermining its long-term sustainability. These examples are not an exhaustive listing, there are many other mechanisms at work through which hazard levels can be exacerbated ranging from over fishing and exposure of coastal fishing populations, to the challenges faced by forest and mountain communities.

It is equally important to highlight that governance and regulation failures with regard to managing a habitat and natural resources in a sustainable manner, can actively shape and compromise the household's ability to mobilize their assets. For instance, across South Asia input intensive farming practices at the local level, largely influenced by the Green revolution regimes, which utilize ground water heavily, have contributed to the alarming rate of ground water depletion across the subcontinent. In addition, the continuous and extensive use of chemical fertilizers and pesticides pollutes rivers, lakes, canals and other sources of fresh water. At the macrolevel, national governments are pressurized to create new settlements, job opportunities and infrastructure, expand the area under agricultural production and invest in rapid industrialization. Again, conservation and the

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4 Very possibly, land ownership and tenure rights may be a more powerful explanatory variable of hazard exposure levels in the first order.

efficient use of natural resources clash with the immediate demand for consumption. Further, there are global pressures to replace traditional food crops with cash crops, and to expand the area under cultivation systems designed for high productivity. These policies are rapidly contributing to degradation of natural resources and intensified conditions for disasters. (ITDG South Asia, 2005)

Finally, communities can aggravate these natural, location and practice-specific factors through disinvestment in physical and social infrastructure at the household (housing materials) and community level (roads and bridges). Both as a result of poor geographic (location), physical and financial capitals. In the case of rural areas, these shortages can be compounded by a high incidence of hazards as a result of being encrusted hazard-prone areas, deepening the susceptibility of households to suffer hazard losses.

Statistical and Econometric Methods

This section puts forward different statistical and econometric methods to assess the proposed working hypothesis. The order of exposition is based on the type of data available that divide mainly into single cross-sections and panel data at different levels of analysis. At this stage, each country team should have already decided the survey and hazard data requirements for carrying analysis with the provided guidelines in Annex II. There will be illustrations of empirical work already done or potentially doable in each case. Three further clarifications should be restated:

1. The proposal is not a template, but rather a general overview of what can be done to better understand the hazard-poverty equation.

2. The proposal does not exhaust the methods to carry out poverty analysis; it only considers those attainable given the frontier of data possibilities (see Annex III).

3. There are some formulations in econometric notation and jargon even though these are kept to a minimum to widen the scope of diffusion of the document.

Three main strands of poverty research will be considered: 1) static poverty analysis that comes from a single cross-section of households or individuals; 2) aggregate poverty trends analysis based on panel at district and subdistrict level; and 3) poverty micro-dynamics that captures the economic mobility of households or individuals, by measuring their well-being at different points in time, most likely two periods (see Table 1). In each block of research, the focus would be on the standard components covered in a poverty study, namely:

- **Identification of poverty,** which consists of categorizing and quantifying distinct groups that emerge from a poverty study (i.e., poor versus non-poor in cross-sectional analysis, or chronic versus transient poor in poverty dynamics), and requires identifying poverty indicators and measuring them;

- **Experience of poverty,** which explores the incidence, depth and severity of static poverty measures, and their temporal analogues for dynamic poverty measures;

- **Explanations of poverty,** which entails generating statements about poverty once the headline figures have been obtained. This is often done through poverty profiles (i.e., descriptive statistics of the characteristics of the poor versus the non-poor) followed by multivariate analysis of the welfare indicator or poverty outcome on multiple correlates (in particular, a statistical regression of the poverty measures on a set of characteristics).[5]

4.1 Static poverty analysis – Hypothesis #1

Identification of poverty

The identification of poverty involves three steps. First, the choice and measurement of a welfare indicator (see Annex II section 2.3). Second, the choice of a means of discriminating between poor and non-poor, typically via a poverty line. This choice stems from the selection of the socially acceptable norm for what constitutes a reasonable level of welfare. Some tend to favour a minimal absolute level of welfare that translates into minimal requirements expressed in a fixed poverty line. Whereas others incline for a relative poverty line in which the researcher sets the welfare norm and thus judges the position of people or households relative to others (Dercon, 2006; Stewart et al., 2007). One should always report the choices made along the way in its construction.

Experience of poverty

Assuming that the poverty line conveys a reliable monetary value for the cost of obtaining a basket of goods and services considered adequate to satisfy a group of basic needs, the final step for measuring poverty involves coming up with a summary statistic that allows comparison across groups. This has been achieved mainly through the adoption of the Foster-Greer-Thorbecke family of poverty indices **(Pα)** widely used in poverty assessments. The generic form is:

$$P(c, z, \alpha) = \frac{1}{N} \sum_{h=1}^{n} , T \left[\frac{(z - c_h)}{z} \right]^{\alpha} \qquad (1)$$

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5 Correlates are characteristics that are found to be closely linked to poverty – for example, family size might be linked to poverty – but no causality pattern can be inferred from their analysis. For example, it is impossible to say whether a family is poor because it is large or whether a family is large because it is poor. On the contrary, determinants of poverty provide information on the causes of poverty and can be analysed by looking at households over time and analysing their welfare changes in light of their characteristics (Coudouel et al., 2002).

Table 1: Proposed quantitative approaches to hazard-poverty analysis			
Data Sources	**Type of Analysis**	**Advantages and Disadvantages**	**References**
Household panel data	Trends in micro-welfare dynamics (poverty transitions) – regressions on level and/or poverty status	**A:** Tracking the well-being of the same individual or household over time makes it possible to estimate changes in their mobility and capture behavioural responses. **A:** Able to identify household-specific factor lost in averaging, required during the analysis of district panel or cross-sectional data. **A:** Non-data demanding (with two rounds could be credibly estimated). **D:** Sample attrition if households cannot be re-interviewed, systematically distorts observed mobility. **D:** Measurement error can lead to overestimation of true movements into and out of poverty. **D:** Ignores dynamics between base and terminal year. **D:** Transition categories might be sensitive to welfare indicator and poverty line.	Baulch and McCulloch (1998); Kedir and Mckay (2005); Herrera and Roubaoud (2005); Bhatta and Sharma (2006); Quisumbing (2007); Premand and Vakis (2008).
	Micro-simulations	**A:** Easy to compute and understand. **D:** Hard to extract insights for policy-making. **D:** Absence of temporal variability.	Dercon and Krishnan (2000); Dercon (2005).
District and subdistrict panel data	Poverty trends analysis – regression on changes in poverty over time	**A:** Dynamic analysis of spatial poverty at subnational level. **A:** Less affected by random measurement error than household panel data due to comparing group-level averages, but if present cannot be corrected. **D:** Focus on average experience of aggregate groups reveals trends for population groups, net aggregate changes. **D:** Neither income mobility nor persistence of poverty can be measured using panel data at this level.	Wodon (1999); World Bank (2004); Ravallion and Loshkin (2005).
District and subdistrict cross-sectional data (poverty maps and census data)	Static poverty analysis – spatial correlations	**A:** Provides disaggregation across groups and regions. **A:** Spatial analysis of poverty with ample breadth of coverage. **A:** Simultaneous display of different dimensions of poverty and/or its determinants. **A:** Overlay multiple sources of data. **D:** No causal inference can be drawn. **D:** Selectivity problems and unobserved heterogeneity.	Henninger and Snel (2002); Lopez-Calva et al. (2005); Bedi, Coudouel and Simler (2005).

Where z is the poverty line, c is the welfare indicator for household h, N is the total population size, and the total sum T is taken only on poor households ordered from bottom to top: $c_1, c_2,…,c_T$. If $\alpha = 0$ then P is equal to the share of the population that is poor. If $\alpha = 1$ then P is equal to the mean distance that separates the poor population from the poverty line, or in other words the depth of poverty. And if $\alpha = 2$ then P is a measure sensitive to the inequality among the poor, meaning that weights are higher as the depth of poverty increases.

Varying explicit and implicit assumptions and decisions are taken along the way to get a poverty measure (the main ones being: equivalence scales, treatment of missing and zero incomes, and poverty lines), leading to varying outcomes. It is therefore good practice to report all choices made in the quantitative treatment of data in terms of the welfare indicators and measures selected, poverty lines and aggregation.

Explanation of poverty

Once poverty is defined over individual households it can be aggregated over N households and make poverty figures available at a subdistrict, district, regional or national level. The next step is tabulating this cross-sectional poverty against a set of characteristics to create a profile. Since this does not allow more than one correlate to vary simultaneously, poverty status regressions are also employed. The obvious problem that arises even for this type of analysis is that at least in the medium to long-run some of those correlates could be the consequence of poverty as much as its causes.

Say, for instance, if a household deemed poor moves into a risk-prone location as a result of its own circumstances then it is likely that there will be an association between hazards and poverty in both directions. This can be addressed with panel data as changes in welfare cannot explain initial household conditions.

4.1.1 Spatial correlations

A starting point of analysis could be to explore spatial correlations between poverty incidence and natural hazards using cross-section data, without implying any causality. While the scope of representativeness of the household surveys from which poverty figures are often retrieved varies across countries, typically these are not representative at district or subdistrict level. Only recently, with the development of new techniques these figures have been brought down to such levels. In those countries where census and household survey data are available for the same year, poverty maps have been developed to illustrate relevant indicators at these levels, including incidence of poverty (P), poverty gaps (P_1), severity of poverty (P_2), inequality, and human development indices (HDIs). (see Annex III for a list of GAR countries with poverty maps). Censuses on their own do not contain income or consumption information with the level of detail required to yield reliable indicators of poverty or inequality within subdistricts; however, they can provide reliable estimates for other welfare indicators, such as health and literacy. This is the case of existing maps for unmet basic needs across countries derived from census data (http://sedac.ciesin.columbia.edu/povmap/).

Supposing the population of a country is divided into k groups of districts, and S_k is the population share in each k_{th} group, any FGT poverty measure can be divided into group contributions as follows:

$$FGT^{\alpha} = \sum_{k=1}^{K} s_k FGT^{\alpha,k} \qquad (2)$$

Where FGT can be expressed as total poverty and K is the total number of districts. Thus aggregate poverty in the country is derived as the population-weighted sum of poverty in each k district.

On the other hand, hazard events or hazard loss variables can be extracted from national hazard databases and then mapped at local levels of aggregation to highlight their geographical and temporal patterns. Most likely, the administrative codes for the areas where this secondary data belong will be similar to those used for an existing poverty

map facilitating an overlay. The equation of risk (hazard loss manifested) states that:

$$\pi_{k\,l} = \sum_{j} H_{k\,j} \cdot E_{k\,l\,j} \cdot S_{k\,l\,j} \qquad (3)$$

Where $\pi_{k\,l}$ is the risk of loss type l (i.e., human, economic, environmental or infrastructure) for each geographic unit k due to various types of hazards j (i.e., flood, earthquake, etc). H is the 'hazard j index' and may be expressed in different forms, for example, the probability of a **hazard j** event of a certain magnitude to occur during a given return period in the geographic unit k; E expresses the total number of elements exposed to a hazard, such as the total population in the case of mortality, the total number of households for losses in the housing sector; a measure like the Gross Domestic Product or Gross Value Added for the economic output, and the equivalent Gross Fixed Capital Formation or Total Capital Stock for capital losses; and S would be the susceptibility index that captures the 'propensity' to get damaged of the elements contained within a given geographical unit and exposed to the hazard.

From the historical datasets at national level, the 'realized' risk in terms of losses during the period of study can be extracted. For an average of 35 years of data for each country this would be the sum of losses l due to the set of events j in geographic unit k. This total damage D can be expressed as follows:

$$\pi_{k\,l} = \sum_{j} H_{k\,j} \cdot E_{k\,l\,j} \cdot S_{k\,l\,j} = \sum_{j} D_{k\,l\,j} \qquad (4)$$

To establish a relevant correlation between hazards and poverty, one must take out the exogenous factors associated with hazard loss. This would allow analysing those aspects strictly attributable to the situation of poverty. The exogenous elements in the above equation are the hazard H and exposure E indices, leaving susceptibility S for analysis:

$$S_{k\,l} = \sum_{j} S_{k\,l\,j} = \frac{\sum_{j} D_{k\,l\,j}}{\sum_{j} H_{k\,j} \cdot E_{k\,l\,j}} \qquad (5)$$

From an operational point of view there are a few aspects to note. First, only three types of losses could be retrieved from the disaster databases: human losses, housing sector losses and agricultural losses (less reliably that the first two). Second, the hazard index data required for this calculation has only been calculated for a few major risks (drought, earthquake, flood, landslide and volcano). National disaster loss datasets contain a wealth of information about many other hazards, including flash floods, heat and cold waves, hurricanes, storms and tornadoes, among others. However, the methodological and theoretical approach for estimating these hazards can be a major undertaking. Instead, the authors propose a simplified methodology that, taking into account the data limitations, will do the following:

- Concentrate on using the 'housing destroyed + housing damaged' fields as key variable for analysis. The interest is not so much to proxy for economic loss, but to focus on a key 'asset' in the livelihoods of both the rural and urban poor.

- Given the lack of hazard index indicators for a large number of hazards in the disaster databases, running the correlations with and without normalizing hazards is suggested.

- To establish the possible correlation between hazards and poverty, the process will be followed over the entire set of hazards and over extensive risk events only. A very significant number of physical hazard-related losses are far more dispersed and extensive over territory, and are far more pervasive over time, with large numbers of frequently occurring events, following a uniform distribution. This justifies the lack of normalization of the hazard index. The equation (5) above would then become:

$$S'_{k\,l} = \sum_j S_{k\,l\,j} \cdot H_{k\,j} \cdot = \frac{\sum_j D_{k\,l\,j}}{\sum_j E_{k\,l\,j}} \qquad (5a)$$

This would be equivalent to taking the sum of losses (for each type of hazard considered) and divide it by a 'normalizing' exposure factor, dependent on the type of hazard considered (assuming a uniform distribution of *extensive risk* hazards over the target geographic units). could be considered as proxy for *S*.

Analysis will then be carried out in two stages, first, normalizing with population only; and second, normalizing by population and hazard index:

1. Using the bulk of data (from all types of hazards) corresponding to both *Intensive and Extensive Risk,* the authors suggest normalizing the loss data (houses damaged +destroyed) using population figures from census or from gridded country population figures using GIS (i.e., converting raster values to vector shape files for each political-administrative area). This method will display a variable of houses damaged and destroyed per year per 100,000 inhabitants used to run a first correlation with poverty data as will be explained below. The researcher might also want to re-run the correlation with 'the rest' of the hazards, which include all the extensive risk events relating to relatively 'endogenous' hazards such as local fires, flash floods and landslides, etc.

2. The second stage of analysis will comprise the following steps:

   a. Normalize the loss data by population as in point 1 above.

   b. Make use of available hazard index data (from UNEP – Preview or from the new Global Risk Update on cyclone, earthquake and flood hazard) to find a correlation between a fully normalized susceptibility index and poverty.

   The composite indicators of hazard *H* and exposure *E* indices could be constructed from geo-referenced data at the lowest point of resolution available for the relevant hazards (i.e., 10x10 or 5x5 km). Then, taking advantage of GIS techniques the researcher can extrapolate the aggregated loss information from the disaster databases over the resolution squares and solve the equation for susceptibility required to run the correlation with poverty. Alternatively, one could extrapolate the information on exposure to hazards by political-administrative units.

   c. Run the correlation with the poverty dataset on hazard losses for **each individual** normalized hazard.

   d. Run the correlation with 'the rest' of those losses that cannot be ascribed to the three normalized hazards (cyclone, earthquake and flood).

This second stage of analysis would enable the researcher to differentiate various levels of correlation by hazard type (for example, it may be that flood losses are far more closely correlated with poverty than earthquake losses).

Overall, the spatial analysis of the endogenous component of natural hazards with poverty maps or census data would therefore be done by indicating correlations as shown below between categories of hazard loss (or hazard type) and identified areas of poverty, say by *k* districts:

$$\Gamma_k_{N\,x\,N} = \rho\,S_{l\,z}\,p_{j\,z}, \text{ where k = 1, ..., K, and z = 1,..., Z.}$$

Where Γ is a correlation matrix with N as the number of different variables on welfare indicators (P, P_1, P_2, HDIs) and the various susceptibility indices created on hazard losses S available for each geographic subunit z contained within the k unit of interest; and ρ as defined below is the correlation coefficient between each susceptibility index S and each poverty indicator p_j for every k unit giving a total of $(Nx[N-1])/2$ unique pairs of correlations:

$$\rho(S\ ,\text{p}) = \frac{\sigma_{\text{S},\text{p}}}{\sqrt{\sigma_\text{S}^2 \sigma_\text{p}^2}} \qquad (6)$$

With $\sigma_{\text{S},\text{p}}$ denoting covariance and $\sigma_\text{S},\sigma_\text{p}$ standard deviations. Finally, one can compare the ranking of p_j poverty mapping measures (or other indicators of well-being) on each k district with hazard impacts computed in any of the above fashions through (Spearman) rank-correlation coefficients. This would require ranking the values of S and p across subunits z contained within each k geographic unit of interest to test the strength of the link between the various series of data. The Spearman rank correlation is similar in spirit to (6), but replacing hazard and poverty loss values with rank values.

Small area data on hazards and poverty could bring important outcomes beyond correlations, including the construction of profiles by regions. The profile may include sectoral and location characteristics (urban/rural, regional distribution) on the poorest and/or more hazard prone states or municipalities; information on the main economic activities and labour markets within them; and the living standards of their populations in terms of health, education, nutrition, and housing. In addition, the geographical distribution of hazards and poverty estimates can be overlaid with geo-referenced data on important community information related with local infrastructure (roads, electricity and telecommunications), health and education facilities and the travel distance to them, as well as natural features, including elevation, rainfall patterns and agro-climatic characteristics. This type of exercise can reinforce any conclusions reached on connections between poverty and geographical areas most likely to suffer from natural hazards.

Although it has been stated enough, there is no harm in reaffirming that an observed correlation between hazards and poverty would not provide conclusive evidence on causal associations. It would confirm relationships that merit closer investigation, but additional studies would be needed.

4.2 Poverty trends analysis – Hypothesis #2

4.2.1 District and subdistrict level regressions

Hazard data can also be connected to regional, district or subdistrict panels constructed from repeated cross-sectional surveys for poverty trend analysis. This would provide more coverage of poverty over time as this type of data are more readily available, but still only looking at average welfare for groups, not households.

Obviously, panels would need to be representative at regional or district level and relatively large. Otherwise, the main problem at this level of analysis is that with so few observations the estimates would have high standard errors making all findings statistically insignificant. One would need to have information on both stratification and clustering so that appropriate standard errors can be computed. Knowing the Primary Sampling Unit to which households belong will help to make a decision whether standard deviations are acceptable for the unit at which analysis is planned.

This would be less of a problem where poverty remapping has been carried out periodically. In such cases, it might be possible to examine how spatial patterns of poverty at subdistrict level co-evolve with other variables over time. While population censuses are usually available every decade, there are cases like Ecuador for which two household surveys and two population censuses have already allowed to create a panel of poverty maps from 1990 and 2001 (Araujo, 2006). There might be instances where supplementary population counts conducted in-between censuses provide the inputs for updating poverty. For instance, in Mexico poverty maps for 2000 have been updated using narrower information produced by a population count in 2005 (Lopez-Calva et al., 2006).

Identification and experience of poverty

Poverty figures at the selected district or subdistrict panel would result from the aggregation of household-level data using appropriate sample weights. The dependent variables constructed could be mean household expenditures per capita, and headcount and depth indices of poverty. For control variables one can construct a number of district (subdistrict) level explanatory variables including the share of individuals, households or localities with a particular characteristic within the district (subdistrict). This might include the proportion of rural-urban population; migration intensity; shares of population working in different economic sectors; age and demographic composition of population; proportion of localities with different types of infrastructure; degree of inequality within the district (subdistrict); etc. (see Table 4). At the regional level, there are numerous

characteristics that might be associated with poverty. In general, however, poverty is high in areas characterized by geographical isolation, a low resource base and other inhospitable climatic conditions, which should ideally be captured as well (World Bank, 2005a). As for hazards, this can be captured as one-off events, or alternatively the cumulative exposure of the district or subdistrict.

Experience of poverty

The evolution of poverty over time at subnational level and its possible association with natural hazards could be assessed in the following fashion: First, compute changes in poverty at the subnational level and test whether these are significant (through two-tail and one-tail tests). The main way of checking whether changes in terms of incidence are statistically significant is testing difference in means relative to their *standard errors*: Samples carry a margin of error, and so do the poverty measures calculated from household surveys. The standard errors depend on the sample design –stratification and clustering, essentially– and the sample size in relationship to the size of the total population (Deaton, 1997). When the standard errors of poverty measures are large, it may well be that small changes in poverty, although observed, are not statistically significant (Coudouel et al., 2002).

Second, get profiles of poverty rates at period *t-1* and *t*, as well as for poverty changes (in those districts or subdistricts where changes were significant) with census-level data. In addition to hazard prevalence, use groups of covariates that are likely to bear an effect on poverty, such as education, labour markets, housing services and facilities, socio-demographic characteristics, and infrastructure (see Table 4). This will highlight major characteristics of poverty (regional distribution, gender, age groups, ethnicity, rural-urban location, etc.), and will help to detect whether new groups of poverty might have arisen, possibly due to the occurrence of natural hazards.

The next step would be to correlate changes in district (subdistrict) poverty rates with a series of initial characteristics (X_{t-1}), including hazards, at the same level of analysis. This would be a more direct approximation (than profiling) to the degree of association between changes in hazard and poverty losses. One may also examine how poverty changes correlate with urban growth rates, demographic trends, trends on environmental degradation, housing conditions, and economic indicators.

Correlation analysis might be suggestive of the importance that some variables play in determining poverty levels and dynamics. Now, hazards may not necessarily raise poverty incidence – their impact will depend on multiple factors, for instance in the case of a drought: in the availability of proper irrigation systems, types of crops cultivated, diversity in occupations of the people subject to rainfall anomalies, and migration rates into and away from affected areas. Controlling for other confounding factors, especially migration, will be necessary. This can happen through multivariate regression analysis between poverty measures for each district (subdistrict) and the large array of observable characteristics mentioned before.

At this stage, the authors propose to inspect the impact of specific past hazard events *(t-1)* on poverty at time *t*, considering that initial hazard losses might condition how the poor benefit from the shares of growth if this occurred at subsequent stages. One would have to first detect the presence of a large-scale disaster through the country hazard profiles. Then link changes in poverty or poverty levels between *t* and *t-1* to hazards and a series of covariates at *t-1*. Changes in consumption poverty for *k* districts (subdistricts) between period *t-1* and *t* can be expressed as follows:

$$\Delta P_k = p(X_{k\,t-1}, \Delta X_k, \Phi_k, HAZARD_{k\,t-1}, \Delta e_k),$$
$$\text{where } \Delta P = P_t - P_{t-1} \qquad (7)$$

Here X represents the bundle of time variant household and district characteristics in district k. ϕ_k is a vector of parameters describing district dummy variables to control for time-invariant characteristics, such as distances to roads, markets, clinics, water supplies, etc., $HAZARD_k$ represents the hazard factors to which the district is exposed and might contribute to differential welfare outcomes observed, and e_k are the residuals.

Function (7) could transform into regression analysis that includes hazard events in the initial period; base-year conditions X_{t-1} on aspects described beforehand, including inequality, human capital, physical capital, region, socio-economic status and economic composition; time-invariant district characteristics encompassed under a vector of dummies D; and changes in the rate of growth and other covariates over the period of analysis. It is particularly relevant to account for migratory dynamics across time and space, considering the population dynamics that a large-scale natural hazard might involve. Population censuses usually contain information on the place of birth of persons, their current residency and place of residency some years prior to the collection of census data allowing the construction of total and recent net migration flows at district level. It is also critical that the welfare measures and poverty thresholds are consistent over time.

$$P_t - P_{t-1} = \alpha + \beta \; \text{HAZARD}_{k \; t-1} +$$
$$B_2 \; X_{k \; t-1} + \beta_3(X_t - X_{t-1}) +$$
$$\beta_4 \, D_{k \; t-1} \; + \Phi_k + \varepsilon_{k \; t} \qquad (8)$$

The specification of the encompassing model could be improved by adding lagged effects on pre-hazard observations in case one would like to test for any evidence of persistence. HAZARD could also be a moving average for hazard losses corresponding to a fixed span of time prior to each period t for which state poverty rates are available. This regression could be estimated for the full sample and then, for instance, by rural and urban areas separately or any other relevant characteristic under study.

If there are enough rounds of time-series observations before and after the hazard analysed, one can attempt a counterfactual assessment of welfare impacts using two methods. First, projecting forward the time series of poverty rates available across each state before the hazard happened and use that prediction as counterfactual to be compared with the actually observed poverty indicator. And second, a regression across districts again to explain growth over the period after the hazard as a function of the estimated impact of the hazard on the base year in each state and controls for pre-hazard trajectories and other covariates (Ravallion and Loshkin, 2005).

Alternatively, function (9) could take the following specification:

$$P_t - P_{t-1} = (X_t - X_{t-1})B +$$
$$X_t(\beta_t - \beta_{t-1}) + (\varepsilon_t - \varepsilon_{t-1}) \qquad (9)$$

Where a change in poverty over time could be explained by changing district characteristics X (which encompass all district-level differences), by changes in their returns to poverty over time (or impact of these characteristics on poverty), and by the remaining district disturbances. Variations over time will be reflected in changes in beta coefficients or parameters.

A final possibility is to use parameters from the regression model obtained for year $t-1$ in order to predict household income or consumption in year t, and to compare this prediction with the prediction obtained using the regression estimates for year t applied to the data for same year t. The differences in the predictions with the two models can then be analysed, and one can test whether changes in welfare between years is due to changes in structural conditions or

changes in the behaviour of households between the two years (Wodon, 2000).

Under the analysis of poverty trends with district or subdistrict panels, the mechanisms that operate at the household level to determine welfare levels are obscured by the aggregations used thus far. Hence, if the aim is to inform about poverty at the microlevel there is still room for introducing improvements.

4.3 Poverty micro-dynamics – Hypothesis #2

4.3.1 Poverty transitions

Identification of poverty

The poverty dynamics literature emulates static poverty analysis up to establishing whether an individual or household is poor or not. After this stage poverty dynamics diverts by qualifying the temporal attributes of poverty. When panels contain two waves (a baseline survey and one resurvey) the analysis is geared towards showing mobility between both waves, usually done through transition matrices.

Box 1: Creating a transition matrix

A transition matrix shows the welfare status for a number or proportion of individuals or households in a base period tabulated against their welfare status in a later terminal period. The categories in the matrix that define such status may be poor/non-poor, absolute income bands or quintiles, among others. The diagonal cells in the matrix represent those occupying the same welfare state *i* in both periods, and the remaining off-diagonal cells represent those who are mobile between periods from state *i* to state *j*. The matrix **T** below shows the absolute number of households for a sample in rural Pakistan entering and exiting poverty between 1986–1988 (Baulch and McCulloch, 1998):

1986/87	Poor	1987/88	
	Poor	**Non-poor**	**Overall**
Poor	67	71	138
Non-poor	80	468	548
Overall	147	539	686

With probabilities of entering poverty state *j* (first below) and exiting poverty state *i* defined as follows:

$$\Pr\left(h_t = j \mid h_{t-1} = i\right) = \frac{N_{it}}{N_{jt-1}}$$

$$\Pr\left(h_t = i \mid h_{t-1} = j\right) = \frac{N_{jt}}{N_{it-1}}$$

Here **N** is the total number of households, and *i* and *j* are states of poverty and non-poverty, respectively. For instance, the probability that a non-poor household in 1986 becomes poor the year after is 0.15 (80/548). Transition matrices and probabilities can be computed for as many sequential dyads as there exist within the panel. The extent of mobility across categories can be further assessed by a series of correlation measures (Glewwe, 2005), with the most popular mobility index **M** for a two-way matrix given by:

$$M(T) = \frac{n - \text{tr}(T)}{n - 1}$$

Where **tr(T)** is the trace of the matrix **T** (sum of elements in its diagonal), *n* is the number of categories (poor and non-poor in **T**), and normalization to make the index take values between 0 (no mobility) and 1 (full mobility) is accomplished by dividing it by **n/n–1** (Shorrocks, 1978). In the case above **M(T)** is 0.66.

Furthermore, one can test whether transitions observed accrue to measurement error in the data or if they are authentic, by comparing the empirical conditional transition matrix with the unconditional matrix. If the expected frequencies for each matrix cell **[(rowtotal*columntotal)/samplesize]** are very close from the actual observed frequencies, it would imply that poverty transitions are unrelated (i.e., the occurrence of poverty in time *t* is independent of the occurrence in *t–1*). In contrast, if the hypothesis of no association is rejected, transitions are meaningful. For a 2x2 matrix, this information can be summarized in a test statistic (Pearson chi-squared) constructed with expected frequencies denoted EXP_{ij} and observed frequencies OBS_{ij} expressed as follows:

$$\chi^2 = \sum_i \sum_j \frac{(OBS_{ij} - EXP_{ij})^2}{EXP_{ij}}$$

Table 2: Selected characteristics in a subsample of rural households in Ethiopia, 1989–1994

Category	Variable	Always poor	Fell into poverty	Moved out of poverty	Always non-poor
Livestock	Value livestock per adult in 1989 in Birr	155.32	550.92	344.72	828.89
Land	Land per adult (1989) in hectares	0.34	0.55	0.42	0.66
Crops	Coffee grown now	0.35	0.15	0.02	0.05
Demographic	Adult equivalent units in household 1989	5.56	4.65	5.42	4.29
Location	All-weather road through village	0.05	0.27	0.36	0.62
Shocks	Rainfall experience (1994 minus 1989)[1]	-0.28	-0.20	-0.11	-0.08

Source: Dercon and Shapiro (2007).

Note: 1) Difference in percentage deviation from mean in 1994 and 1989. Deviations relative to long-term mean for main season in area. This is a measure of how good the last main season preceding the 1994 survey was relative to the last main season preceding the 1989 survey round (the more negative this difference, the worst the recent season).

Explanation of poverty

With results on the households who have been poor or non-poor in both periods along with the number who have escaped poverty and those who have entered poverty, poverty profiles can be constructed for each particular category. The profiles can bring in those indicators of most interest, including geographical regions, rural/urban residence, household and community characteristics, and the occurrence of natural hazards. For instance, drawing on two rounds of panel data (1989 and 1994–1995) for 354 households in rural Ethiopia, Dercon (2006) breaks down four resulting poverty groups by a number of characteristics to find that those remaining poor and those becoming poor suffered the highest incidence of meagre rains in this period, while the best rains in the long-run were for those turning non-poor.

Multivariate regression analysis is commended as the next step to improve the above type of analysis. A poverty status regression can be built to determine whether the occurrence of a hazard is significantly associated with the probability of being poor or non-poor. This is typically accomplished using binomial probabilistic models (probit or logit models – also called binary response models) in which the dichotomous variable (Y) representing the state of poverty or non-poverty is regressed over a set of supposedly exogenous explanatory variables, including hazards, to model its probability of happening (i.e., probability of Y equalling one). The choice of the logistic versus probabilistic models formally depends on the structure of the error term, with the latter assuming a normal distribution. Precisely because of this link to the normal distribution, the probit model is slightly preferred and can be expressed as follows:

$$\Pr(Y_h = 1 \mid X) = \Phi(\alpha + \beta' X_h) \qquad (10)$$

Where $Y_h = 1$ if the household has become poor and $Y_h = 0$ if not. X_h is the vector of independent explanatory variables (either continuous or discrete or both) and $\Phi(.)$ is the cumulative normal density function. Hence, if x_j were to be a continuous variable (rainfall precipitation), its partial effect on $\Pr(Y=1|X)$ (i.e., the effect on the probability of becoming poor if rainfall increases) would be given by (11) below. If x_h were a discrete explanatory variable, say the occurrence of a drought by switching from being 0 to 1, the partial effect on $\Pr(y=1|X)$ (i.e., the effect on the probability of becoming poor if a drought is experienced), would be given by the non-marginal change in expectations (12):

$$\frac{\partial E(Y)}{\partial(x_j)} = \phi(\hat{\beta}' \overline{X})\hat{\beta}_j \qquad (11)$$

$$\frac{\partial E(Y)}{\partial(x_j)} = \underbrace{\phi(\hat{\beta}' \overline{X})\hat{\beta}_j}_{X_j=1} \quad \underbrace{\phi(\hat{\beta}' \overline{X})\hat{\beta}_j}_{X_j=0} \qquad (12)$$

Where $\varnothing(\beta'X)$ is a standard normal density function evaluated at $\beta'X$. The coefficients in probit specifications represent the marginal effect of variables at the mean of the distribution. But the functional form of the relationship between natural hazards (when captured as a continuous variable) and predicted household poverty is of greater interest. It is therefore desirable to calculate marginal effects of, say, rainfall precipitation at different parts of the distribution and for a range of values for other independent variables of interest.

Unlike the two-round analysis of consumption poverty that mainly considers transitions from poverty to non-poverty and vice versa, one can credibly throw in some extra categories, including those staying out and remaining in poverty, when the outcome of interest pertains to non-money metric indicators, such as nutrition or health. One can model probabilities of entering, exiting, remaining or

staying out of poverty based on status regression again and then establish whether a hazard may have a differentiated impact depending on the poverty transition in turn.

The researcher may want to know whether hazards are only relevant for entering poverty or can also affect chronic poverty. The most straightforward way to do this is the multinomial logit model that extends the logic for analysing binary or dichotomous variables (0 – non-poor, 1 – poor) into the analysis of categorical variables with more than two sets of k parameters (1 – non-poor, 2 – former poor, 3 – new poor, and 4 – chronic poor).

This model would be interested in estimating the probability that the *ith* household belongs to the poverty transition state j (j= never poor, exit from poverty, enter into poverty and chronic poor) relative to one category left out (i.e., one category of the poverty transitions variable is chosen as the comparison category). Making these probabilities a function of hazards experienced by household i and some household and community characteristics, if option 1 is the base alternative (non-poor), its probability can be expressed as (13) while the probability that *ith* household is in any other poverty status would be (13a):

$$\Pr_{ij}(Y_{i1} = 1 \mid x_i) \quad = \frac{1}{1 + \sum_{j=2}^{4} e^{\beta_j' X_i}} \quad = \quad \frac{1}{1 + \Pr(\text{former poor}) + \Pr(\text{new poor}) + \Pr(\text{chronic poor})} \qquad (13)$$

$$\Pr_{ij}(Y_{ik} = 1 \mid x_i) \quad = \frac{e^{\beta_k' X_i}}{1 + \sum_{j=2}^{4} e^{\beta_j' X_i}} \text{ , for } 5 > k > 1 \qquad (13a)$$

Box 2: Asset poverty transitions

Identification of poverty

Poverty transitions could also be used to assess the effect of hazards on assets in a quantitative way. The crucial step lies in the identification of poverty (i.e., establishing the threshold for asset poverty). One way of setting the asset poverty line is at the median of assets for households under the poverty line (although this requires relying on monetary poverty for identification). For instance, in rural areas, this could happen through Tropical Livestock Units (TLUs), which are standard ratios that approximate the value of a full range of animals relative to one unit of livestock obtained from their respective weight, subsistence and market values (i.e., 1 TLU = 1 cattle = 0.5 horse/donkey or mule = 0.1 goat/sheep, etc). This can also be done with housing or farming tools (Carter et al., 2007; Porter and Dercon, 2007). One can then work out asset transitions matrices among different categories of households, as well as asset poverty transitions.

Experience of poverty

The researcher can characterize the experience of asset poverty through the same attributes of money-metric poverty (incidence, depth and severity) using, for instance, livestock monetary values. Alternatively, in line with the literature on money-metric poverty, the researcher can treat asset poverty as a dichotomous (yes/no) variable, ignoring its depth or severity.

Explanation of poverty

Having created binary indicators for a whole set of asset poverty indicators (nutrition, health, education, livestock) one can investigate the susceptibility of falling into this situation as a result of hazards. For instance, in the case of nutrition poverty one would control for a full set of other correlates (child and mother characteristics, housing and spatial location).[6]

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6   More sophisticated analysis has been done under dynamic asset poverty traps, which set a threshold of assets below which households stay on low-level welfare equilibrium or go into a downward trajectory. This asset threshold is not simple to operationalize and may be liable to criticism for its narrowness. It is uni-dimensional being expressed mostly in terms of asset values, when in fact thresholds could be multi-dimensional, affecting empirical analysis (Dercon, 2007a). There is also no systematic development of empirical strategies to identify poverty dynamics and critical asset thresholds, which might explain the scant evidence on this type of work to date (Barrett et al., 2007).

Here X_i is the vector of household and community-specific characteristics relating to household i, and β corresponds to the parameters that describe being in j_{th} poverty transition status. This exponential beta coefficients represent the change in odds of being in the poverty status category (i.e., being chronic poor) versus the comparison category associated with a one unit change in the dependent variable.

The multinomial logit model works under the assumption that the various transition states are independent of each others' outcomes. For instance, the probability of entering poverty should have no relative impact on the probability of being chronic poor relative to never been poor. Intuitively, one might expect that some factors driving households into poverty are unrelated to those keeping them in that state permanently. But for this type of analysis it is essential to ensure that this is the case more formally through a statistical test. Its logic is quite simple, but details are omitted for space reasons (see Hausman and McFadden, 1984).

The loss of information that results from collapsing consumption, incomes or any other welfare indicator into binary categories remains a valid concern, but it is believed that modelling poverty transitions makes sense for assessing the impact of natural hazards on poverty, as the hazards are expected to raise the probabilities for entering into or prolonging hardship. Another factor that qualifies the validity of the poverty transitions approach is the presence of measurement error, but in fact binding consumption can limit the biased caused by measurement error. Moreover, panel data allows using methods that assess and minimize – or correct – measurement error (see Glewwe and Gibson, 2006).

It has been also suggested that defining transition categories might produce arbitrary results to the extent that estimates are sensitive to the poverty lines and the choice of the welfare indicator. But again, if the poverty line is set at a meaningful absolute level it would be valuable to continue doing poverty transition analysis (Lawson et al., 2003). In addition, the researcher can inspect changes and trends in transitions matrices brought about by the use of alternative poverty lines to determine whether poverty transitions are sensitive to the choice of benchmarks.

A second way to estimate the effects of natural hazards on households across time when two rounds of panel data are available is to look at changes in outcome levels (e.g., changes in consumption), rather than converting them into dichotomous categories. This in practice would avoid throwing away useful information contained in the inter-temporal variation of the outcome (Baulch and McCulloch, 1998).

A first candidate would be the standard household consumption smoothing analysis in mean levels of consumption. Here one can regress some measure of changes in welfare (i.e., consumption expenditures) on sources of hazards to determine if their realization (or variation) can account for a significant proportion of variation in expenditure. However, unlike this type of exercise that often ignores the initial and ending position in the welfare distribution, the idea would be to restrict attention to the downside impacts on those groups affected by poverty. A very generic form to illustrate how this could be done is the following:

$$\Delta c_{h\,t} = \sum_v \beta_{1\,h} \mathrm{HAZARD}_{h\,t} +$$
$$\beta_{2\,h}\,(\mathrm{P}_{h\,t-1} * \mathrm{HAZARD}_{t\text{-}1\,h}) +$$
$$\beta_{3\,v}\mathrm{D}_v + \beta_{4\,h}\mathrm{X}_{t\,h} + \varepsilon_h \qquad (14)$$

Where $\Delta c_{h\,t}$ is the change in consumption levels (or the growth rate in total consumption per capita of household h in period t if consumption is expressed in logarithmic form). HAZARD denotes the occurrence of hazards between periods $t\text{-}1$ and t, which can be treated in different ways (household hazard data or rainfall records or both) as explained in section 4.1.2. D_v stands for a set of dummy variables identifying each community separately (regional dummies for locality level fixed effects), and X being the vector of household characteristics. P is a dummy variable taking the value of 1 for poor households with some observed characteristic (i.e., land hectares below the median of their respective locality) and 0 for households lying above. Lastly, ε_h is a household-specific time-invariant error term capturing unobservable components of household preferences (fixed tastes or technology effects).

If interest lies in testing whether a group of households can keep consumption smooth after being affected by a hazard it would suffice to measure (14) without estimating β_2. With a sample composed by impoverished villages (i.e., low-income beneficiaries targeted for a social programme), the coefficient summarizing the partial covariance between hazard and consumption (β_1) would already indicate the resilience of poor households (Skoufias, 2003). However, this specification would be insufficient to test whether consumption of poorer households may be affected by hazards as opposed to better endowed households. Fully considering equation (14) would allow capturing more explicitly the group-specific effects of hazards. In principle, one would choose some observable and preferably time invariant characteristic, say landholdings in rural areas or education of the head in an urban setting. Then classify households into poor or non-poor (i.e., land-poor versus land-rich households) on the basis of such attribute relative to the

median in their respective community. This dichotomous variable could then be interacted with hazards to capture household- or group-specific abilities to deal with them once regressing consumption over the full set of community and household controls.[7]

The above analysis could be accomplished on samples where the majority of or all households are below a minimum welfare benchmark (as is the case for programme evaluation samples targeted at poor constituencies) or within a broader population. Alternatively, one can make a distinction between rich and poor households in the sample along some asset category, or more generally stratify the sample on the basis of some characteristic before the hazard event and then estimate equation (15) separately for each group, making sure this is not liable to problems of endogeneity (two-way causality) (Hoddinott and Kinsey, 2001; Hoddinott and Quisumbing, 2003; Quisumbing, 2007).

Gender-based analysis could also be accomplished in this fashion. While this should ideally be undertaken individually, data rarely exists as poverty measures are typically at household level and per capita analysis rarely captures gender differentials. Nevertheless, female-headed household are often a poor proxy for this and thus, this is one measure that can be used when censuses or large enough sample data sets are available.

An alternative procedure to assess the effects of hazards on poverty levels is to estimate regressions on per capita household consumption (or its natural logarithm) evaluated at different parts of its distribution. This could be done through quantile regression, with quantiles corresponding to each poverty transition category (Quisumbing, 2007). A quantile regression model is preferred over a discrete choice model method when one wishes to disentangle the relative influence of hazards at different parts of the welfare distribution, and even has some advantages over conventional ordinary least squares (OLS) techniques. While OLS methods estimate changes at the mean of the distribution, and are not robust to outliers or heteroscedasticity (i.e., when the random variables have different variances leading to wrong inference), quantile regression follows a least-absolute deviations technique based on the weighted sum of the absolute errors, giving

less weight to outliers. And as opposed to OLS modelling, the quantile regression estimates the marginal effects of covariates at a given quantile of the distribution rather than the mean. Suppose the interest lies on finding whether a flood might affect consumption more severely for those entering into poverty than the rest of groups. This could be accomplished in the following way:

1. Sort the sample observations based on the welfare outcome (i.e., consumption).

2. A quantile refers to the general case where sample observations are divided into given percentage parts, often determined by the researcher. In the case of poverty transitions, a possible break would be given by the quantile corresponding to the mean value of consumption for each poverty transition category (i.e., never poor, moving into or exiting poverty, always poor) (Quisumbing, 2007).

3. This would imply estimating four regression curves each corresponding to the four categories above to consider the effects of a set of household and community characteristics over time (vector $\mathbf{X}$) evaluated near the bottom of the distribution (in the case of chronic poverty), median (moving into or exiting poverty) and end (never poor).

4. For each regression, the optimization problem would be set as trying to find the regression line that minimizes the weighted sum of absolute deviations that result from the difference between every observed welfare outcome and the value predicted by the model as shown below:

$$\frac{1}{N}\sum_{i=1}^{n}\rho_{\theta}\left|Y_i - X_i{}'\beta\right| \qquad (15)$$

The ρ_θ is a weighting function to 'centre' the data and depends on the quantile of interest. This idea of 'centring' data means that if the quantile of interest is below the median, deviations likely to be far away from the regression line will be given less weight so that the minimization process takes place around this quantile. This idea can be expressed more clearly as follows:

$$\varphi_{\mathrm{q}} = -(1-q)\sum_{y \leq x'\beta}(y_i - X_i{}'\beta) + q\sum_{y > x'\beta}(y_i - X_i\beta) \quad (16)$$

Where $0 < q < 1$ is the quantile of interest, y_i are the consumption outcomes, and $X_i\beta$ is a parametric function. The weights can be different for positive and negative residuals. If both types of residuals are weighted

in the same way, then one obtains a median regression. Shifting the weight will decide whether minimization is tried to be achieved at the first or third quartile, for instance.

5. The coefficient estimates for the hazard variable(s) in the above function can be obtained through linear programming methods.

4.3.2 Micro-simulations

One can also gauge the impact of hazards on income or consumption poverty in cross-sectional data by linking predicted consumption levels to varying hazard scenarios. This would obviously require a good hazard distribution for the period and population under analysis.[8] In practice, this would entail omitting observed hazard realizations to create counterfactual distributions of the welfare indicator and then observe its effect on poverty. The first step would be to estimate a regression on consumption, which can take various forms depending on the type of hazards observed. A generic form to express this would be:

$$\hat{c}_h = \sum_v \beta_{1\,v} \text{HAZARD}_h +$$
$$\sum_h \beta_{2\,h} \text{HAZARD}_v +$$
$$\beta_{3\,v}(\text{D})_v + \beta_{4\,h}\text{X}_h + \varepsilon_h \qquad (17)$$

Here $\hat{c}_h$ is predicted consumption, **HAZARD** denotes the occurrence of hazards prior to the date of the survey, and subscripts h and v whether this hazard hits the household or village, respectively. D_v stands for a set of dummy variables identifying each community in the survey separately (regional dummies for locality effects), and X being the vector of household and community characteristics. Lastly, the vector of parameters to be estimated is β, and ε_h is a household-specific error term.

One could map whether the incidence and scope of hazards have a differentiated effect on poverty from direct pre-coded questions to the main respondent in the household questionnaire. In this case, HAZARD_h would be the existing

vector of hazard data. Provided there is access to secondary or indirect measures of hazards (i.e., rainfall and temperature records, or perhaps hazard loss databases) instead of direct information from household surveys, the researcher can map them into consumption poverty after properly matching those rainfall records into the communities under study (Christiaensen and Subbarao, 2004). HAZARD_v would be the only vector of hazard data available in this case. Finally, both of the above sources can be combined to come up with a more complete hazard distribution of each household to inform the variance of consumption as in Dercon and Krishnan (2000) and de la Fuente (2005).

Running an OLS regression of consumption levels (or its logarithm) on any combination of the above vector(s) of hazards can give a pre-figuration of their impact on consumption and, in consequence, poverty levels. For instance, Dercon, Hoddinott and Woldehanna (2005) found in a regression linking consumption per adult to rural households in Ethiopia in 2004 to a series of hazards and other household and community time-invariant conditions that reporting a drought in the two previous years was correlated with 16 percent lower consumption (mainly food consumption), and a drought experienced four years before reduced consumption by 14 percent.

With the parameter estimates of consumption readily available, the welfare outcome can be predicted for the case in which the shocks would not have occurred (vector $\text{HAZARD H}_h = \text{H}_v = 0$). If consumption had been calculated under vector HAZARD_v above one could also predict the counterfactual situation with rainfall at a given percent below its mean level or a combination of bad household-level hazards reported as dichotomous variables ($\text{HAZARD}_h = 1$) with poor rainfall in equation (17). The computation of poverty rates from alternative predicted scenarios would simply result from plugging in the predicted values $\hat{c}$ in the relevant poverty measure.

$$\hat{P}(\hat{c}, z, \alpha) = \frac{1}{N} \sum_{h=1}^{n}, T\left[\frac{(z - \hat{c}_h)}{z}\right]^\alpha \qquad (18)$$

The vector of poverty rates that ensue would allow observing the contribution of each significant hazard to overall poverty. Following on this idea, Dercon (2005) grouped the most significant hazards in the data for rural Ethiopia mentioned above into 'drought', 'markets' (increase in input prices or decrease in output prices, and lack of demand for agricultural products) and 'illness' (death or illness of head, spouse or other member), and using the head count index of poverty came up with a series of poverty figures. Drought shocks had the most serious impact, contributing the largest share of transient poverty in this period. Predicted poverty was

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8   The presence of a good retrospective module on the history of natural disasters and where individuals recall their ancestors past welfare can be another alternative to work with cross-sectional data. The authors choose not to elaborate further on this aspect, first, because there are no surveys with good retrospective modules in the selected country studies; and second, many researchers do not regard this as a credible method for collecting quantitative data given that people tend to develop selective memories over time (Addison, Hulme and Kanbur, 2008).

about one third higher due to their occurrence (see Table 3). In this type of computation it is important that unobserved heterogeneity (things that can shape consumption, but are not observed and differ across households) is not correlated with the hazard variables; otherwise consumption might pick up some of these aspects devaluing the validity of the method to illustrate the impact of hazards on poverty.

Table 3: The impact of shocks in 1999–2004 on poverty in rural Ethiopia in 2004	
	Head count
Actual poverty	47.3
Predicted poverty	43.8
Predicted poverty without drought shocks	33.1
Predicted poverty without illness shocks	40.4
Predicted poverty without input/output markets shocks	41.2
Predicted poverty without shocks	29.4

Source: Dercon (2005).

5 Conclusion

Country studies will have to take decisions regarding four key issues to inform on the relationship between hazards and poverty from a quantitative perspective.

1. Nature of survey (cross-section or panel) and hazard data employed (hazard databases, rainfall) based on the quality of data available and the purposes of research.

With regard to the household surveys, the most likely options are to carry out single or combined analysis with following sources:

- Cross-sectional data, without being able to control for unobserved household-specific effects, but covering a great deal of spatial conditions within countries;

- District or subdistrict panels to follow poverty trends at an aggregate level and gauge the impact of policy responses on them, but at the expense of not having valuable information on household behavioural responses; and

- Household panel to model welfare micro-dynamics, but given the data constraints of research, one would be looking at most one period ahead from the baseline survey. While better for modelling dynamics, the sunk costs of investing in panel data and possibly not finding meaningful associations given this temporal narrowness as opposed to quick setup through cross-sectional analysis should be considered. Most likely, the bulk of the country analysis would be undertaken using methods suitable for single and repeated cross-sectional data, whereas panel data analysis will be undertaken for a small set of countries.

2. Available indicator(s) of well-being.

Consumption is the preferred welfare measure employed by poverty studies and most likely will be found in the GAR country-study surveys. Yet, it is still true that a number of factors make current consumption a noisy welfare indicator as well. In that sense, the study can certainly be related to other dimensions such as education, nutrition and health, or even a relationship between assets and hazards can be brought into full consideration.

3. Estimation decisions and implementation – motivations and rationale.

Once a welfare measure has been chosen, the next step will be to set a specification for the purpose of exploring the mutual relationship between poverty and natural hazards. An empirical model consistent with the framework outlined would be one that makes a household's welfare depend on several factors such as household asset levels, household composition, some community and district characteristics, plus a number of hazard indicators or their impacts. Spatial correlation analysis is proposed to explore the mutual relationship between hazards and poverty. To identify more specific contributions of hazards to poverty, one should attempt regression analysis considering the dependent variable in the form of levels, changes in levels or binary form.

4. Outcomes presented.

Some deliverables expected from the GAR country case studies are climatic and geological hazard profiles of the country or region assessed; an explicit reference as to whether any of the proposed hypotheses for the study has been corroborated, expanded or rejected; and possible explanations for this. In the build up for reporting the main findings, it would also be desirable to find reported possible motivations for choosing the dataset in turn, indicators of well-being, and estimation decisions.

Annex I – Concepts and Definitions

1.1 Hazard

Hazards (risk in economics literature) are potentially damaging physical events or phenomenon that may cause the loss of life or injury, property damage, social and economic disruption, or environmental degradation (ISDR, 2007). The first part of this definition shows that the probability of occurrence of hazards is associated with a threat to welfare until they materialize or vanish. This allows to point out that households can have some sense of the likelihood of events occurring *a priori* (i.e., can attach a probabilistic outcome to the hazard), without really having any direct control over them (i.e., they are not perfectly certain that will occur in any given future). The impacts resulting from the hazard will depend on the related exposure and vulnerability[9] of a given population, which can be summarized by household and community endowments (see Figure 1).

The above characterization has important implications for analysing the temporal nexus of hazards with poverty. Being exposed to a hazard *per se* can be welfare damaging in the sense that households due to risk-averse behaviour typically adopt less than optimal income-generating activities to reduce this exposure, which in low-income contexts can translate into poverty, even if the hazard event never materializes. Simultaneously, if a contingency occurs, since the poor tend to lack adequate access to financial and social insurance institutions, they usually end up using their few assets, which could plunge them further into persistent deprivation. Therefore, the effect of hazards on poverty could be understood from two temporal angles with respect to the hazard itself: before it happens (*ex ante*) or once it occurs (*ex post* assessment). The route of analysis taken in this proposal (and therefore proposed for the country case studies) is in the latter fashion (i.e., once the hazard manifests

explore its effect on poverty as an *ex post* backward-looking exercise).[10]

1.1.1 Typology

Hazards can be conveniently classified according to their origin into two broad categories: natural, including earthquakes (geological), droughts (weather-induced), and epidemics (epidemiological); and/or human induced, such as financial crisis (economic), ethnic, gender or religious discrimination (political), civil strife and war (social), nuclear hazard (technological), and pollution and deforestation (environmental) (World Bank, 2000; ISDR, 2007). This proposal focuses on natural hazards associated with geological and climatic factors. This comprise earthquakes, tsunamis and volcanic eruptions in the first case; and cyclones, droughts, floods, hurricanes, mudslides and typhoons, in the second case.

In addition, the scope, frequency, length, strength and degree of autocorrelation with other hazards can vary widely across natural hazards having different implications for poverty. For instance, a flood can affect isolated individuals or households living on the edge of a community remaining highly idiosyncratic, while similar rains in another state can strike entire groups of households in various communities or regions becoming covariate. Torrential rains can occur frequently while volcanic eruptions are rarer. However, a volcanic eruption despite being infrequent and short-spanned can have catastrophic effects as opposed to long-spanned, but less intense floods. Likewise, one-off events such as a hurricane will have different implications than an extended hazard as the case of droughts. This paper makes use of all this terminology to characterize natural hazards. Finally, the impact of natural hazards can compound over time with others. Hurricanes might reduce the people's capacity to withstand other hazards in the future such as droughts. If shocks concatenate and lead into further hazards (i.e., earthquakes leading to fires, floods and landslides), they will be highly auto-correlated (Siegel and Alwang, 1999; World Development Report 2000; Lavell, 2000; Sinha, Lipton and Yaqub, 2002; UNDP, 2004; ISDR, 2007).

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9   This proposal avoids the concept of vulnerability for two reasons: It might lead to confusion as practitioners from different disciplines use different meanings and concepts of vulnerability, which, in turn, have led to diverse methods of measurement and frameworks to understand it (Alwang et al., 2001). Second, the concept of vulnerability is not as well developed as that of poverty, at least within economics. And even then, there seems to be an increasing agreement that should remain a forward-looking concept associated to a negative welfare outcome (Hoddinott and Quisumbing, 2003). This brings practical difficulties to map the effect of hazards on poverty.

10 With some exceptions (Ligon and Schechter, 2003), mapping the effect of a covariate welfare-damaging event (with backward-looking data) on future poverty has been done without quantifying the welfare loss associated with its possible realization. Therefore *ex ante* forward-looking measures are not considered in the analysis.

1.2 Poverty

An individual, household or community is said to be poor when it falls short of a level of welfare deemed to constitute a reasonable minimum, either in some absolute sense or by the standards of a specific society (Lipton and Ravallion, 1995). Poverty encompasses four overarching dimensions that need to be spelled out to confine the empirical and methodological reach of this proposal: 1) breadth and multidimensionality; 2) depth and severity; 3) duration; and 4) spatial distribution (Clark and Hulme, 2005).

1.2.1. Breadth and multidimensionality

The conventional aspects of people's lives that are used to determine a situation of poverty are money-metric measures such as income or consumption, at least within economics. The most commonly used poverty measures are food insecurity (calorie-based) headcount measures mapped onto consumption expenditures. It has also been common to incorporate into such expenditure variables other basic needs (i.e. nutrition and health, including proxies like water supply, sanitation and education, and more rarely energy, durables and rents). However, these other aspects of welfare should have been gradually included in the study of poverty through their own metrics rather than compressing them into consumption expenditures (Kanbur and Squire, 1999). In that sense, rather than reinforcing the idea that consumption poverty is the only desirable measure of welfare, emphasis on different dimensions of well-being –potentially liable to damage while households or individuals are struck by natural hazards – is encouraged while conducting analysis for the GAR report. It should also be stressed that headcount measures in any of this aspects is very different from measures of depth and skewness, which as explained below are distributional measures that can be applied to each of these dimensions of poverty.

The established truism with respect to the multidimensional nature of poverty has been followed by methodological and theoretical considerations and proposals to measure such breadth (Bourguignon and Chakravarty, 2003; Duclos et al., 2006; Alkire and Foster, 2007), some of which are still unfolding. While promising, most of these applications are still waiting to be endorsed empirically. In poverty dynamics, multidimensional concepts and measures of poverty lie even further behind or are simply not there yet (Addisson, Hulme and Kanbur, 2008). Therefore, this proposal considers safer ground to assess the effects of natural hazards on poverty looking at single dimensions of poverty (and explore distributional issues within them when deemed convenient by the researcher).

1.2.2 Depth

The measurement of poverty has been constantly refined. It has progressed from counting the poor towards capturing the severity of poverty (i.e., the extent to which welfare falls below any given threshold) as well as its distribution across the units of analysis (Foster, Greer and Thorbecke, 1984; Clark and Hulme, 2005). All three aspects add something different to our understanding of poverty and have become part of the standard toolkit for its assessment. As a result, exploring the incidence, depth and severity of poverty should be part of the analysis on the effects of natural hazards on poverty.

The above dimensions have translated into measures that capture the extent to which consumption, and income to a lesser extent – as dominating indicators in poverty measurement – fall below the poverty line on average as well as their distribution (inequality). Nevertheless, there is no impediment for this practice to be translated into other spaces. If child malnutrition were the poverty indicator of interest, then normalized values (z-scores) for stunting and wasting below -2 or -3 standard deviations (depending on the severity of malnutrition) would represent the threshold against which specific stunting and wasting outcomes for children would be assessed (see Table 5). Aggregation would ensue by simply counting the number of children below this norm (Dercon, 2006).

1.2.3 Duration

Traditionally, time has been included in poverty analysis in terms of poverty trends and historical accounts of poverty. For instance, a typical statement would be: poverty in country A was 20 percent in 1990 and dropped to 15 percent two years after. While this poverty trend contrasts headcounts of poverty snapshots across A in two points in time, it says nothing on whether the observed 15 percent of poor households was the same over both periods of time or if new households left or entered into this group in-between periods.

This major shortcoming has given rise to the poverty dynamics literature that distinguishes between transitory and chronic poor, and the factors correlated with the observed mobility or lack of mobility, respectively. The two basic ways of modelling inter-temporal poverty dynamics are the spells approach that focuses on transitions from one welfare status (poor/non-poor) to another (non-poor/poor); and the components approach that breaks down welfare into permanent and transitory components. Both types of approaches only make sense when more than two waves of panel observations are available. This represents a major constraint in the GAR countries as only three of them have

panels with more than two waves of data (see Annex III).[11] For this reason, this proposal mainly considers mobility when two waves of panel data are available (a baseline survey and one resurvey).

This proposal also gives consideration to static poverty analysis coming from a single cross-section of households and the analysis of poverty trends based on a series of longitudinal cross-sections. As discussed below, time-invariant poverty analysis cannot be informative about the effects of natural hazards on poverty trends. However, a nationally representative cross-section can provide a good geographical overview of the diversity of living conditions of households within a country. This can give way to the analysis of spatial patterns of poverty (arguably another dimension of poverty) and their possible association with hazard patterns if the survey can be supplemented with databases for all major hazard types, including earthquakes (GSHAP), flooding (Dartmouth Flood observatory), along with rainfall records that provide data on meteorological drought/flooding.

1.3 Assets

The exposure of households to poverty and natural hazards may have an important connection with their access to assets and the way people call on them, along with the liabilities that may exercise claims on family resources, such as being in debt. Therefore, clarifying the concept of assets is important. The definition and categorization of assets is detailed in Annex II section 2.2.

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11 The **spells approach** defines the chronically poor as those who are poor in every wave as opposed to the transitorily poor who might cross the poverty line (or other welfare boundary) through the period of study. It receives its name from counting the number of periods (or 'spells') in poverty that a person or household experiences. The approach has two main failings. First, it ignores that some spells are in progress when the panel starts and ends (i.e. censored), when in fact the span and timing under poverty or non-poverty should matter. And second, it ignores dynamics between the base and terminal years, and hence does not distinguish between transitory and permanent trend effects or trajectories (Dercon and Krishnan, 2000; Oduro, 2002). These shortcomings give birth to **modelling poverty dynamics through components** that isolates statistically the permanent component of a household's welfare from any transitory fluctuations around the permanent level, by modelling the welfare indicator itself. The extent to which the permanent component falls below the poverty line is the degree of chronic poverty since deviations in poverty around the permanent level are seen as transitory poverty. This approach has also important shortcomings: First, it requires large time-periods as its estimation involves averaging consumption over time. And second, it can render a less intuitive notion of chronic poverty as this can result from one-period poverty in multiple periods due to averaging. The two approaches are not equivalent. The poverty spells approach distinguishes chronically poor people from other people in general (because the categories are not all beyond a well-being benchmark), whereas the component approach distinguishes between people's chronic poverty from its transitory poverty.

Annex II – Data Sources

To test the aforementioned hypotheses in section 2, one requires information on three fronts:

1. Natural hazards, with an identification of their context-specific frequency, scope and severity, when possible;

2. Existing household, community and extra-community assets; and

3. Welfare outcomes that, crudely speaking, result from the interaction of the first two and can span from money-metrics to human development indicators.

Most data for components 2 and 3 is contained, or can be elicited from household and community surveys and censuses. Occasionally, information on the incidence, impact and responses to natural disasters might be encompassed in surveys. However, this will still be missing by and large in the surveys of the selected country studies (see Annex III). Therefore, secondary hazard-related data, such as historical hazard databases, rainfall records from meteorological stations or satellite technology as well as seismological data, should also be integrated into quantitative work to model natural disasters and their impact on poverty.

2.1 Hazard data

2.1.1 Household surveys

Climatic and geological hazard data at household level would enable the consideration of differentiated poverty experiences on the basis of their occurrence. This matching will be less relevant while looking at how poverty helps to configure the exposure of human settlements to hazard damage.

Information on natural hazards at household level would capture events as perceived by households irrespective of their scale. This could redress the neglect that more frequent, but less intensive hazards experience relative to large-scale catastrophes. At the same time, once the number of hazard-affected households within a locality is known the researcher can get a sense of its scope rather than assuming that all hazards are *de facto* covariate and will affect everyone simultaneously.[12] For instance, a series of droughts, earthquakes, floods, frosts and hurricanes experienced by a sample of rural households in Central Mexico between 1998 and 2000 were for most part of the period quite idiosyncratic (de la Fuente, 2005).

If hazard information is available in longitudinal form, the analysis can concentrate on their persistence in household's welfare dynamics. With hazards recorded in consecutive periods of time the researcher can also get an estimate of whether successive calamities (i.e., hazard bunching) had a higher impact on welfare outcomes. Obviously, there should be an effort to control for the potential trade-off between the number of consecutive disasters experienced and their respective intensities. This requirement is not unattainable, but the hazard module contained in the survey would require that respondents quantify the impact of the peril in monetary terms to proxy its magnitude. For example, the percentage of their wealth, income or consumption that was lost, or the cost of any damage done by the hazard (Carter et al., 2006).

Other caveats of survey hazard data to keep in mind are the time lags that hazard questions work with (Did your household experienced a drought in the last six months?). The survey could miss important events, especially one-off large-scale disasters unless it was conducted for that purpose. The infrequency can complicate the study of extreme impacts on poverty trends over time. This shortcoming could be attenuated by the importance that the GAR wants to concede to low-profile hazards as well. The lagged nature of hazard questions in household surveys may also imply not capturing their date of occurrence and length, making comparisons across hazards fairly uneven. For

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12 To distinguish the scope of weather-related hazards one can follow the procedure suggested by Tesliuc and Lindert in Guatemala (2002), which consists in counting the number of households within each locality to aggregate them at the locality level; then, estimate the proportion of households reporting the incidence of the shock in each locality. Finally, estimate the proportion of villages with a small, medium, or large share of households that reported experiencing the hazard. One can also get a sense of the extent to which hazards are common or idiosyncratic by looking at the contribution of the village effects in the total variance of the indicator. This can be achieved by decomposing the variance of each hazard event allowing for time-varying village level means on a pooled dataset across survey rounds. In practice, the village-level variance is like the R^2 of a regression on a full set of time-varying village level dummies (Dercon and Krishnan, 2000; de la Fuente, 2005).

instance, floods happening six months ago or a week before the interview date will be lumped into one single period, possibly clouding their impact on poverty in the first case. A household may have suffered a flood five months ago and the income reported may have already recovered to some extent from the shock. For this reason, ideally comparisons should be made 'like-with-like' (i.e., assess the flood impact over the same group of people within the survey).

Second, hazard answers are typically converted into dichotomous variables, which imply modelling them as if they were of the same magnitude, even though their impact could be very different across households. As Tesliuc and Lindert (2002) pointed out from their data for hazards in Guatemala: given that unlike consumption, hazards in surveys do not have their own measurement unit, it is possible that the same qualitative response (Did you experience a flood? Yes or No) masks heterogeneous responses. This deficiency could be corrected with more detailed information on hazard impacts as suggested above and not simply dichotomizing answers. It remains to see whether modules with these characteristics exist inside the household surveys considered for this project (see Annex III).

Finally, as all self-reported information, hazard answers are subject to respondent bias or self-attributed causality. This means that certain groups are more likely to report certain hazards for reasons related with their own characteristics rather than for being more affected, with the possibility that better-off families complain more than poor respondents about any hazard (Hoddinott and Quisumbing, 2003; Hoogeveen et al., 2004; de la Fuente and Fuentes, 2007). This has been more clearly observed for idiosyncratic illness episodes, and only in a few cases for natural disasters (Quisumbing, 2007). The potential reporting bias should be verified on a case-by-case basis by cross-tabulating responses with wealth indicators and other information on relevant categories found in the household survey.

In sum, household surveys containing data on natural hazards (including programme evaluation samples) can make an assessment of their effect on poverty much more informative. Thus, it is worth paying special attention to those sources that deal with them explicitly, without neglecting the sorts of problems that can be encountered in their quantification.

2.1.2 Secondary sources

In those instances where household surveys (main input for poverty assessments) and programme evaluation samples have no information on natural hazards, it will be essential to bring in alternative sources of data, including national hazard databases, rainfall records and seismological data. And even when valuable climatic and geological data is in place at the household level, in the current state of most surveys

it is extremely difficult to capture some of their attributes, especially their severity (de Weerdt, 2006).

National hazard databases

Each country considered for this assessment will have at its disposal national hazard loss databases containing the following features over a 25-year period on average: the date of occurrence and location (at subnational political-administrative units) of a wide range of natural hazards; and the extent of their severity, mainly measured through impacts on three categories of losses (houses damaged and destroyed, hectares of crops lost, and mortality rates).

The advantages of such databases are self-evident: First, they can convey the inter-temporal dimension of hazards (including seasonal and monthly variations) as well as their spatial component at lower levels of observation compared to global hazard databases like EM-DAT.[13] Second, the higher resolution will capture manifestations of frequent small-scale hazard events, including fires, flash floods, landslides and storms, associated with climatic hazards. And third, they capture the severity of hazard, which constitutes a most relevant, but highly elusive attribute.[14]

In principle, this information can be assembled with survey and census data for two different purposes. First, to cross-validate hazard accounts contained in household survey data or to convert other valuable sources of information, such as rainfall records, into meaningful hazard events.

Second, provided the administrative codes are the same for the areas in which hazard and poverty data were collected (i.e., district level), and considering that the analysis of exposure to hazard events is carried out at subnational level, the availability of hazard incidence and impacts can be overlapped to cross-sectional data in an effort to indicate correlations with identified areas of rural or urban poverty by hazard type and loss category. Some contextual variables might not be accounted for in the above analysis. In particular, if poverty data is only available for one particular time interval, what would that interval imply in the overall context of a period of intense accumulation of hazards? What are the dynamics of settlement and migration in the area in question over the period of intense hazard accumulation and

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13 EM-DAT (Emergency Events Database) contains data entries from 1900 through the present, and registers events as disasters if they produced 10 or more deaths, affect 100 or more people, or where a situation of emergency was declared or a call for international assistance was made. Most losses associated with frequent, but small-scale scenarios are below these loss thresholds, and therefore, are not documented in the database. Finally, it has a global level of observation and a national scale of resolution (ISDR, 2007).

14 This last feature will still be difficult for hazards that have no established scales e.g. flooding, storm surge. But for rainfall, a deciles-based method could be used as a working method.

prior to the interval in which poverty data was collected? These aspects would be beyond the scope of the exercises proposed here, and at best can be captured qualitatively.

This second line of analysis will not be able to move beyond correlations towards the establishment of meaningful causalities, but will facilitate the location of spatial trends, if any. In fact, when panel data is available at district or subdistrict level, hazard databases can be used to assess the hazard effects on poverty trends at this level of analysis (see section 4.2).

In a similar vein, hazard data at district level can be employed to capture welfare dynamics or impacts on human development indicators of certain groups by interspersing hazard events in-between two periods for which outcome data is available. There are various issues to consider while connecting hazard data to household surveys for analysing poverty. First, the level at which this imputation will happen is beyond households implicitly assuming that everyone is being affected. And second, there will be a restricted period of observation as most panels in GAR countries comprise two rounds spanning from the second half of the nineties to the first part of this decade. This narrowness might impede to capture large-scale highly infrequent catastrophes that are more likely to cause noticeable poverty. Ultimately, this is an empirical matter, but the sunk costs of setting up a panel data at the household level combined with the possibility of not capturing observable hazard effects on poverty for the above reasons should be borne in mind. This fact reinforced the authors' decision to leave out of this proposal two common ways of modelling inter-temporal dynamics (spells and components) as the three household surveys with more than two waves of data within the GAR countries have no hazard modules in them (see Annex III).

Beyond the different ways of connecting hazard data for analysis, there is a key issue to be addressed that refers to whether the hazard event itself or its impacts should be used as the key variable to represent the effect of natural hazards on poverty. There is an argument in favour of using impacts to capture the severity of hazards; however, the reporting of some impacts might be fundamentally endogenous to the livelihoods of the population under analysis. If this were the case, one cannot ascertain to what extent the severity of the calamity and not the individual capacity of households to cope with it are responsible for the observed outcomes. Take the cases of Peru and Japan where despite similar patterns of natural hazards, fatalities average 2,900 a year in Peru but just 63 in Japan (World Bank, 2000). Most likely these figures are a combination of earthquake severity and the households' capacity to cope with them.

In its extreme version, a selection problem might crop up if the least or most able families exit the hazard-affected community, distorting any possible appreciation of its real severity. Suppose two contiguous communities experience a flood of similar intensity. In community A, many people decide to leave due to their inability to stand the rains leading to an underreporting of only 2 households affected. By contrast, in community B characterized by more economically dynamic households, those who decide to move on to avoid constant floods will leave behind the most vulnerable. The reported impact will throw 10 households affected giving the impression of a highly more devastating flood in B.

The presence of 'selective attrition' affecting community-level hazard loss variables can be problematic for any cross-sectional analysis of causality in household survey and census data because there is no full proof way of determining the existence or direction of the effect. Longitudinal data can offer more scope to address this concern by looking at the profile of attritors and the possible motivations that led them to migrate (Hoddinott and Quisumbing, 2003).

Another critical issue is whether impact information in hazard databases was recorded only for those events with reported impacts. The evidence of losses implies that hazards must be present, but there could be natural hazards with no impacts reported or at least not in the categories mentioned before (i.e., housing and crops). Obviously, only a re-run of the raw data on a case-by-case basis by the country teams will tell how many large intensity events report no loss, typically because of poor newspaper reports that are an important source for DesInventar. In survey data, the impact of climatic and geological events could be used to take advantage of the more precise answer of what experiencing a hazard meant for households. Moreover, it should be possible to verify the potential mismatch between events and their consequences by looking at the percentage of households with registered impacts for each event (de la Fuente, 2005).

Unlike the effect of hazard loss on poverty or vice versa, the presence of endogeneity in hazard events themselves can be controlled for in survey analysis. Poverty might configure the propensity to experience losses giving the impression that some natural hazards are endogenous. For instance, strictly speaking a volcanic eruption would be fundamentally exogenous, but fires in a squatter settlement fundamentally endogenous, and other hazards, such as earthquakes, floods or hurricanes usually in-between. However, the propensity of a hurricane or earthquake for causing material damage and trigger poverty may be controlled through initial household- and village-level characteristics alone and interacted with hazards. In other words, the problems of endogeneity that may arise in the sense that poorer households may be expected to experience a higher incidence of natural hazards than affluent counterparts can be controlled through wealth indicators. Location is a different matter. The researcher would need to carefully verify if, for instance, spatial position makes some households more susceptible to agro-climatic

hazards than others. This proposal considers that hazard events as exogenous variables in their origin deserve special consideration for analysis.

Rainfall and seismological records

An alternative way to capture the intensity of hazard events is through units of measurement associated with the phenomenon in turn – rainfall for drought and floods, temperature for frosts, earthquake magnitude, and so forth. In doing so, the focus on severity is switched from hazard losses to hazard inputs and is exogenous to household coping mechanisms, mending potential troubles contained in some of the impact-based indicators of hazard severity discussed above, in particular mortality.

In addition, climatic and seismological data may complement the absence of locally covariate hazard information in household surveys. In principle, community questionnaires can provide data related to locality-specific hazards. However, retrieving the degree of aggregation or the severity of hazards from this piece of data is often impossible, and since the respondent is habitually a community representative the self-attribution of causality in his/her response might crop up again.

In contrast, one can compile a detailed account of rainfall records expressed on a monthly basis for a given period of years coming from meteorological stations or satellites. Once available, this data can be matched to the geographical position of the localities under study. At this point it would be necessary to establish whether rainfall matters over a span of time or only for a specific month(s) during the period under analysis. For this purpose, the cross-matching of hazard databases with rainfall records can pinpoint the dates (historical occurrence) of relevant hazards and their length, avoiding the need to make wrong calls on when to consider rainfall deviations a hazard event. Indicators can be created on the extent to which monthly rainfall magnitudes in percentage terms are above or below the long-run means for the respective localities (say for capturing a flood) or on median rainfall precipitation for a given interlude (in the case of a drought). If daily precipitation databases exist at decent spatial resolution a number of small-scale and highly-localized hazards, such as flash floods, can also be stochastically modelled from conventional meteorological catalogues (World Bank, 2005b).

Each step above involves some degree of circumspection. The researcher needs to make sure that rainfall data covers the relevant geographic areas of analysis – the whole country or a region. In rural areas, rainfall stations might simply not be there or have low quality and insufficient data in regions with low potential and limited commercial farming interests (most likely poor geographically inaccessible areas). In addition, rainfall data tends to be available at different

geographical units or boundaries than those of the survey, making interpolation necessary. Topography can pose a great difficulty for matching mean rainfall data in places liable to microclimates with large differences in weather patterns within a few kilometres (i.e., when stations are encrusted in mountains characterized by drops of various hundred of metres over a few kilometres) (Hoddinott and Quisumbing, 2003). Both shortage of stations and location can create a potential mismatch between rainfall data to proxy hazard severity and poverty. Fixing this problem is not insurmountable, but would require a careful effort to integrate data into the locality frame and make findings meaningful (for instance, GIS can help in developing appropriate smoothing algorithms and spatial models).[15]

Needless to say, this task will not be possible for hazards without relevant measurement units, including tsunamis and volcanic eruptions. However, many small-scale and highly-localized hazards cannot be generated easily from conventional seismological and meteorological catalogues (mudslides and debris flows, localized flash floods). In these cases, the national historical databases may provide the only source of information on the full range of hazard events within countries.

2.2 Asset data

The second source of information required to determine the extent to which households mitigate hazard impacts is linked to assets. Household assets are the stock of wealth used to generate well-being (Siegel and Alwang, 1999). The usefulness of coping strategies during times of stress has to do with the ownership and accumulation of different types of assets, but also with the capacity to mobilize them. This appendix focuses on the former aspect, which is more widely available in household surveys. Clearly, it would be desirable to conduct an analysis of returns and transformation of different types of income-earning assets during hardships,

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15 A study of vulnerability to poverty in 506 localities of Central Mexico made use of rainfall data expressed on a monthly basis for a period of 40 years (from 1961 through 2000) coming from meteorological stations spread across the localities under study. Given the highly demanding nature of data and the fact that most of the stations did not correspond to delimited political boundaries, it was necessary to perform imputations in the following way: 1) create correlation matrices between core rainfall stations (those next to localities and with the highest number of observations) and the rest to identify pair wise secondary stations based on the highest correlations observed; 2) calculate the respective long-run means for both types of stations; 3) compute the corresponding mean ratios assuming then that the variability in the records is the same across stations, but not the mean; and 4) interpolate values multiplying the values of the secondary stations by the means ratio to scale them (de la Fuente, 2005).

but will be hard to attain given the information at disposal and the time constrains faced during research.[16]

2.2.1 Household-level data

This proposal refers to tangible assets to designate natural, human, physical and financial capitals, and intangible assets to designate social and political capital. Human capital alludes to the level of education (literacy and years of completed education) and health condition (nutritional and disease status) of household members. Both groups of indicators are instrumental to raising individual income-generating capacities, but also reflect welfare in their own right. Hence, they can be used as dependent variables in the poverty-hazards analysis (see section 2.3). The household composition in terms of its size, sex and life-cycle of its members as well as their occupations (especially for the head) will be encompassed under household characteristics. Physical capital can be associated with productive assets such as land, cultivated areas, working tools, equipment and work animals (in rural areas), and with housing size and type of materials, and household services (especially important for the urban poor as productive asset or investment); or stocks including livestock, food, jewellery, household appliances and other durable goods. Finally, financial capital refers to cash, savings and access to credit.

Intangible assets are understood in the traditional sense of social, institutional and political relationships among households within and outside the community, including gender relations, social ties and networks (proxied by inter-household transfers), participation in associations and organizations, and intra-household relations (Moser, 1998). Clearly, the mapping of this group of variables into appropriate indicators for their quantitative measurement is more difficult.

2.2.2 Community-level data

The capacity of households to mobilize their assets during natural hazards has a direct connection with the broader context in which these are deployed (i.e., existing structures of opportunity at the community level). This refers to the institutional support that can complement or replace household coping strategies (i.e., safety nets), as well as the provision of infrastructure and services from government institutions to the community. In particular, the existence of

physical and social infrastructure (and in some instances the proximity or distance to those facilities) at the community and extra-community level is fundamental for rural and urban communities alike, as it influences the availability and accessibility to goods and services from the state and markets. This includes safe and dependable water supply system, sanitation and drainage, schools, health clinics, marketplace, local administrative centres, transportation and communication infrastructure, protection and enhancement of the natural asset 'commons', and storage facilities. This information collected from 'community questionnaires' on local infrastructure, health and education facilities, added to market prices, can be valuable for eliciting the returns to assets and their utilization. However, community surveys alongside household data are not always available.

At the community level, geographical and environmental capital influences the availability of natural and communal resources as well as the connections of the community with the regional and macro economies. This can determine the comparative advantage of the community or, by the contrary, increase its predisposition to suffer damage or loss when exposed to hazard events. These capitals include land, water, trees and so on, but also the climatic conditions that result from location. In addition, one can incorporate GIS/mapping software to produce a spatial representation of existing variables such as terrain, agro-ecological zone, distance from major cities, etc.

Households interacting with each other inside the community and beyond portray some sort of assets that result from this interaction. For instance, households can strengthen linkages with other communities participating in marriage and migration, but also being part of inclusive political systems and markets (Siegel and Alwang, 1999). While the commons are important in practice, they might be rather difficult to break out from the sum of household assets without intense empirical research.

2.2.3 Census and administrative data

Undertaking the analysis of poverty on hazard losses will have to consider information beyond the community level. A combination of secondary sources, such as administrative data and information collected by government statistical services, in particular census data can become a prime source.

Some indicators beyond community level that could be considered for poverty analysis at district or subdistrict level would result from the aggregation of individual, household or community data. For instance, the degree of geographical isolation (availability of roads and paths usable at all time of the year) per district; average availability of public services and human resources, access to employment and share of economic activities of its population; land distribution;

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16 The usefulness of assets when it comes to coping with natural hazards goes beyond their ownership and households having access to them. To generate income in case of hardship, assets need to have a high return and be liquid (readily available to be transformed into cash). Typically high return assets are more risky posing a trade-off in the type of asset held. For instance, livestock is usually highly illiquid and hard to mobilize. In a similar vein, the fact that assets can hold their value during times of stress (being stores of wealth and saving to manage risk) is an important attribute that needs to be considered when assessing specific assets. When a common hazard occurs, incomes are low and returns to different assets become low, often negative.

and degree of inequality across gender, racial or ethnic lines inside the district.

Overall, data on human, physical, financial and social capital, combined with information on the functioning and opportunities in product, labour and asset markets, could provide a good basis for identifying vulnerable households to natural hazards. The main categories of data for collection appear below:

Table 4: Asset data needs at household, community and extra-community level			
Asset Type	**Individual/household level**	**Community level**	**Extra-community level**
Natural	Availability and quality of 'private' land, pasture, water.	Availability of 'common' land, pasture, forests, fisheries, water.	Availability and quality of types of land, rivers and watersheds.
Human	Household size, composition (sex and age) and occupation of members. Dependency ratio. Literacy and schooling, and health and nutritional status of household members. Proportion of adults employed in household.	Share of working population. Labour pool. Main productive activities in locality.	Share of rural-urban population. Rate of urbanization. Share of population by economic sector. Weight and spatial distribution of productive activities. Age and demographic composition of population. Literacy rates and shares having various levels of schooling.
Physical	Productive assets (tools, equipment, work animals, plot size and type of land access). Housing size, type of materials and services. Household goods and utensils, food, jewellery.	Productive assets (communal and private). Stocks (livestock, food).	Productive assets (rental markets). Stocks (e.g., buffer stocks).
Financial	Cash, savings, access to credit and insurance markets.	Access to financial and risk-pooling Community-based Organizations (CBOs).	Access to credit and insurance markets.
Social and Political	Membership or participation in CBOs. Inter-household transfers. Degree of trust in neighbours.	Number of CBOs in community. Rate of migration incidence. Proportion of households with extra-community social ties and networks. Indicators of governance.	Rate of migration incidence. Degree of inequality along gender, racial, ethnic lines. Indicators of regional governance.
Location and Infrastructure	Proximity and access to water and sanitation, education and health facilities, marketplace storage, tarmac roads.	Availability of and proximity to schools, health centres, marketplace, storage facilities, roads, bridges, water and sanitation.	Distance to national markets, transportation and communication. Proportion of localities within district with different types of physical and social infrastructure.

Sources: Siegel and Alwang (1999) and World Bank (2005a).

2.3 Welfare outcomes data

2.3.1. Money-metric indicators

In quantitative work, the conventional aspects of people's lives that are used to determine a condition of poverty are income or consumption. This choice stems from their tractability and easy operationalization. Among them, consumption is usually preferred over income for the following reasons:

1. It is a better outcome indicator – Actual consumption is more closely related to a person's well-being in the sense of having enough to meet current basic needs, whereas income is only one of the elements that will allow consumption of goods (others include questions of access, availability, etc.);

2. It may better reflect a household's ability to meet basic needs – Consumption expenditures reflect not only the goods and services that a household can command based on its current income, but also whether that household can access credit or insurance markets at times when current income is low or even negative. Consumption can therefore provide a better picture of actual living standards than current income, especially when income fluctuates a lot; and

3. It may be better measured than income – Especially in poor agrarian economies, incomes for rural households may fluctuate during the year, in line with the harvest cycle. This implies that it may be difficult for households to correctly recall their income, making the information on income of low quality. Finally, large shares of income are not monetized if households consume their own production or exchange it for some other goods.

But even if consumption is the chosen measure, there are a number of factors that should be borne in mind. First, people in general will not prefer constant consumption over the life-cycle. In fact, different households may face different constraints on their consumption smoothing. Poor people tend to be more constrained than the non-poor in their borrowing options, so that not only lifetime wealth, but its distribution over the life-cycle affects lifetime welfare. Second, even if current consumption varies less around long-term well-being than current income for a given household, it may not be the best ordinal indicator to convey long-term living standards. And finally, even if better measured than income, it is still bound to some measurement error.

The degree of sophistication in the construction of the expenditure variable depends on the information available. Most studies divide consumption into food and non-food (transportation, personal and household hygiene, clothing, education, health, and durable goods) components, and report expenditures per capita to account for the number of members sharing resources inside the household. This has to be so as income and consumption are typically only observed at the household level. A further refinement is often achieved by employing adult equivalent scales that are weighs used by age and gender to adjust for different household structures. Put together, the above adjustments render comparability of poverty outcomes across households of different size and composition.

2.3.2 Non-money-metric indicators

While focusing on income or consumption flows can facilitate the analysis of poverty, their use for assessing the effect of hazards on well-being is not always self-evident. For instance, extending the analysis of poverty transitions into non-income dimensions provided they display some change over time can report the following advantages:

- The presence of measurement error in consumption and income data leading to spurious fluctuations in welfare might be attenuated with the use of information on human or physical capital.

- If the aim is to capture the persistence of poverty, it might be more relevant to focus on those aspects that determine the structural capacity of household to earn a living. This would include household human and physical capital (anthropometric measures and material asset levels), rather than flows that are more volatile over short-time periods, especially in the context of poor households (Clark and Hulme, 2005).

- It makes sense to centre attention on assets given that assets themselves are often the main target of natural hazards.

Provided any other dimension of well-being can be properly quantified, say health or nutrition, there is no impediment for taking up morbidity and poor nutritional status as core indicators of poverty. In both cases, international benchmarks can be called on to assist the definition of poverty. The researcher can identify 'poverty lines' for health, nutritional and educational deprivation for children and adults. For children, one can use stunting (height for age) and wasting (weight for height) as indicators of nutritional deprivation, whereas for adults 18 years and older, the body mass index. For stunting the z-score is calculated as the height for a child minus the median height of an international reference standard (of well nourished children of the same age and sex), divided by the standard deviation of that reference standard. As for wasting, the median reference value is calculated as the quotient between the weight of a given child and the median weight for a given child of that height. Finally, the body mass index is obtained by dividing weight in kilogramme by the height in centimetres squared of individuals. Under-nutrition (or nutrition poverty) can be defined as being below a z-score of -2 for children (meaning that given age and sex, the child's height is two standard deviations below the median child in that age/sex group) or

being below a body mass index of 18.5 for adults (Hoddinott and Kinsey, 2001).

One can also compute moderate (severe) education poverty in terms of literacy or schooling attainment, but obviously the resulting categorization is clearly more arbitrary and context specific. For instance, Gunther and Klasen (2007) defined educational poverty for Vietnamese adults of 16+ years as having less than 9 (4) years of education, which was equivalent to completed lower secondary school and primary school, respectively. Moderate education poverty for children aged 6–15 years was defined as having dropped out of school within the first 9 (4) years.

The choice of human development indicators will not be exempt of controversy and pitfalls. The two main drawbacks to consider are that many non-income dimensions of well-being do not change much over time and often seem to exhibit a great deal of inertia in the sense that usually measure improvements. And second, that most current survey instruments lack the tools to systematically track poverty in the non-income dimension or simply miss this type of information. For instance, a compilation of 28 panel datasets in developing countries found that 23 of them assess the standard of living in terms of income or consumption (Lawson, McKay and Moore, 2005).

Table 5: Poverty indicators proposed for analysis

Dimension	Indicator	Definition	Computation
Consumption/ Income	Incidence	Household unable to afford a basket of goods and services considered adequate to satisfy a group of basic needs.	Normalized ratio of coverage of minimal needs (based on self-reported consumption over constructed poverty line) transformed into dichotomous variable to signal poverty ($=1$).
	Depth	Extent to which household welfare falls below any given threshold (poverty line).	Normalized ratio of coverage of minimal needs (values between 0–1).
	Inequality	Distribution of welfare across poor households.	Normalized ratio of coverage of minimal needs squared (weights are higher as the depth of poverty increases).
Nutrition	Stunting	Indication of chronic under-nutrition.	Anthropometric measure of height-for-age that falls two standard deviations (z-scores) below the international reference mean.
	Wasting	Indication of acute under-nutrition.	Anthropometric measure of weight-for-height that falls two standard deviations (z-scores) below the international reference mean.
	Body Mass Index	Indication of under and over-nutrition for adults between the ages of 18 and 60 years.	Anthropometric measure of weight in kilogramme divided by the height in centimetres squared of individuals aged 18–60.
Education	Literacy	Individual illiterate in reading and writing.	Self-reported literacy.
	Schooling Attainment	Not having achieved primary-level education.	Self-reported years of school completed.

2.4 Types of household surveys available[17]

In principle, the question(s) of interest driving each country study should lead to the methods and data employed. For instance, if the concern lies on short-term hazard-led welfare fluctuations, two waves of data might suffice. But if interest revolves around their potential to keep people on a low-level steady state of welfare (i.e., create chronic poverty) clearly the data requirements will be more stringent. For this reason, any consideration of the association between natural hazards and poverty should start from an assessment of the informational basis available.

In terms of household surveys for poverty analysis, there is a continuum that goes from cross-sections with detailed data on household characteristics, consumption expenditures, and in some cases income, towards multi-thematic panels that include modules on climatic hazards, household risk management and coping mechanisms. In between both extremes, multiple combinations can take place (i.e., cross-sectional data with multiple modules, sometimes even on hazards) and certainly in this space is where most of the current surveys stand.

2.4.1 Single cross-sectional data

Static poverty analysis comes from a single cross-section of individuals or households. This could be a representative sample at some level of aggregation or a full population in the case of a census. If the aim is to follow the effect of a hazard on the same unit over time either of these are obviously ill-suited. That said, they constitute the most common source of household data at hand and are most suitable for studying the interaction between natural hazards and poverty from a spatial perspective given their ability to capture the diversity of household living conditions within a country. For instance, the integration of detailed information on income and consumption from household surveys with census data has brought to fruition the creation of poverty maps down at subnational level in countries like Peru, Guatemala, Ecuador, Mexico, Nepal and Sri Lanka (see Annex III).[18]

2.4.2 District and subdistrict panel data

A succession of cross-sections can become a panel at the level for which sampling has been defined (i.e., rural/urban, regional or district level), and therefore add some dynamism to the analysis of poverty by allowing to consider changes in poverty. It might even be possible to analyse poverty dynamics at subdistrict level where poverty maps have been updated. While this exercise is more difficult given that population census are usually available every decade, there might be instances where inter-censal population counts provide the inputs for updating poverty (Lopez-Calva et al., 2006). The averaging that results from getting aggregate poverty figures may also conceal measurement errors in welfare outcomes at the household level, refining estimations of changes in aggregate poverty figures (McKay and Lawson, 2003).

At this level of analysis one could assess the impact of state or regional policies that could block (exacerbate) the effects of hazards on poverty, for instance, economic (distortions on) growth or (non)redistributive policies implemented to reduce inequality.

Obviously the examination of poverty experiences across groups would only hold when the same sampling frame is used for both cross-sections and the clusters remain relatively homogenous (Hoddinott and Quisumbing, 2003). The downside of this approach is that household samples differ from year to year cancelling the possibility to focus on the welfare experiences for the same group of individuals or households.

2.4.3 Household panel data

Unlike the above sources of data, panel datasets tracking the well-being of the same individual or household over time make possible the estimation of changes in their mobility, while controlling for household-specific factors – observed and unobserved[19] – that might impinge on poverty.

Despite being most suitable for modelling poverty dynamics, panel data also presents important caveats that need to be considered and, if daunting, corrected while conducting an analysis of this nature. A first problem is measurement error in the outcome of interest that could exaggerate dynamics since not all the observed inter-temporal variation would be ascribed to mobility. This is particularly acute when the analysis is based on already difficult to measure data such as consumption and income, but it could well happen with anthropometrics. The presence of measurement error in the

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17 For a thorough discussion on pros and cons of different types of data sources for risk-related welfare analysis see Hoddinott and Quisumbing (2003).

18 Briefly, poverty mapping involves, first, discovering relationships between household characteristics and the welfare level of households as revealed by the analysis of a detailed living standards measurement survey. And second, applying a model of these relationships to data on the same household characteristics contained in a national census to determine the welfare level of all households in the census. The resulting estimates of household welfare and poverty derived from the census are spatially disaggregated to a much higher degree than is possible using survey information (Benson, 2002; Elbers et al., 2004; Bedi, Coudouel and Simler, 2007).

19 To control for household-specific unobserved factors that may affect outcomes (for instance, psychological resilience of household members or their motivation to strive forward) one needs to assume that those factors are fixed over time, and that those households that remain in the sample do not differ from those who have left (Hoddinott and Quisumbing, 2003).

welfare indicator is often credited to its recompilation or construction. Other sources could be inappropriate price deflation or misuse of adult equivalence scales (Kamanou and Morduch, 2002).

A second source of trouble arises when households drop out from the panel in a non-random fashion (attrition). This can happen either because they are very dynamic (better endowed and thus move elsewhere) or extremely precarious to the point of physical extinction or implosion in the form of breakup or migration. On the contrary, if the loss of households occurs in a non-systematic way there should be no cause of concern other than shrinking the sample size (Dercon and Shapiro, 2007; McKay and Lawson, 2003; Hoddinott and Quisumbing, 2003; Kamanou and Morduch, 2002; Baulch and Hoddinott, 2000; Yabub, 2000).[20]

For space reasons, this proposal does not elaborate on the techniques developed to capture the presence and extent of measurement error or attrition, nor the solutions to address them. There are ways to adjust for the presence of substantial measurement error (Glewwe, 2005). As for attrition, it would be good practice to report the rate of attrition, compare profiles between attritors and non-attritors, as well as discuss possible determinants of attrition, and carry out probabilistic models to estimate the probability of attrition from the survey conditional on initial household characteristics (Dercon and Shapiro, 2007; Glewwe and Gibson, 2005; Fitzgerald, Gottschalk and Moffitt, 1998).

While these limitations of panel data must be taken seriously, this proposal recommends panel data to be considered as their effect can be mitigated. More importantly, panel data will provide information on household behavioural responses to natural hazards that would otherwise be absent at the other levels of analysis proposed.

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20 The analysis of welfare dynamics may also be affected by the choice of the poverty line. This choice may have an unpredictable effect on the number of people who move into and out of poverty from period to period. One way of establishing the robustness of the poverty dynamics encountered (sensitivity of results to the choice of poverty line) is by conducting regression analysis of the transition categories on correlates for a range of poverty lines (Baulch and McCulloch, 2003).

Risk–Poverty data availability for Latin American case studies

Country	Data for monetary and non-monetary poverty measurements	Time	Geographic unit	Social indicators at geographic unit	Years	Are there panel surveys?	Do they contain data on shocks?
Bolivia	Encuesta Integrada de hogares (EHPM)	–	National (rural-urban)		1993		
	Encuesta Nacional de Empleo	–	National (rural-urban)		1997		
	Encuesta de hogares – Programa Medición de condiciones de vida	Annual	National (rural-urban)	Yes	1999–2002		
	Encuesta continua de Hogares	Annual	National (rural-urban) Capital cities	Yes	2003–2006	No	No
	Census	–	National (rural-urban) By state (rural-urban) Municipality (rural-urban) Locality (rural-urban) Regional (rural-urban)	Yes	2001		

Country	Data for monetary and non-monetary poverty measurements	Time	Geographic unit	Social indicators at geographic unit	Years	Are there panel surveys?	Do they contain data on shocks?
Colombia	Pobreza Monetaria: Encuesta de Ingresos y Gastos (poverty lines)	–	National (rural-urban) By state (rural-urban)		Last in 1994		
	Encuesta a Hogares	Annual	National (rural-urban) By state (rural-urban)		1974–2000	Yes	
	Encuesta Continua	Monthly	National (rural-urban) By state (rural-urban)		January 2000 –June 2006	Impact evaluation surveys from the Familias en Acción Program (2002, 2003, 2006)	Yes
	Census	–	National (rural-urban) By state (rural-urban) Municipality (rural-urban)	Yes	1964, 1973, 1985, 1993, 2005		
	Encuestas de Calidad de Vida	Every 5 years	–		2003, 2007, 2008		

Country	Data for monetary and non-monetary poverty measurements	Time	Geographic unit	Social indicators at geographic unit	Years	Are there panel surveys?	Do they contain data on shocks?
El Salvador	Encuesta de Hogares de Propósitos Múltiples (EHPM)	Annual from 2000	National (rural-urban) By state 50 municipalities	Yes	1991, 1998, 2000–2006		
	Census	–	National (rural-urban) By state (rural-urban) Municipality (rural-urban) Locality (rural-urban) Regional (rural-urban)	Yes	1971, 1992, 2007	No	No

Country	Data for monetary and non-monetary poverty measurements	Time	Geographic unit	Social indicators at geographic unit	Years	Are there panel surveys?	Do they contain data on shocks?
México	Encuesta Nacional de Ingreso y Gasto de los Hogares (ENIGH)	Every 2 years	National (rural-urban)	Yes	1989–2005, 2006		Yes, both The Progresa/ Oportunidades survey contains one module with questions on shocks. This survey is asked to poor rural and urban households only.
	Census and Conteos	Every 5 years	National (rural-urban) By state (rural-urban) Municipality (rural-urban) Locality (rural-urban) Regional (rural-urban)	Yes	1995, 2000, 2005	Yes ENNViH and Progresa/ Oportunidades	
	Poverty Map	–	By state Municipality		2000, 2005		

Country	Data for monetary and non-monetary poverty measurements	Time	Geographic unit	Social indicators at geographic unit	Years	Are there panel surveys?	Do they contain data on shocks?
Peru	Encuesta Nacional de Hogares (ENAHO)	Annual	National (rural-urban) By state (rural-urban)	Yes	1995–2006		ENAHO includes one module with questions on adverse situations faced by the household during the last 12 months (2001-2006)
	Encuesta Nacional de Hogares sobre Mediciones de Niveles de Vida (ENNIV)	–	Regional (rural-urban)	Yes	1985, 1991, 1994, 1996, 1997, 2000	Yes ENAHO ENNIV	
	Poverty Map	–	District		2001		

Risk–Poverty data availability for Asian case studies

Data sources	Nepal	Iran	Sri Lanka	Orissa	Tamil Nadu
All disasters	DesInventar (1980s–2006)				
Urban disasters	No				
Household panel data with shocks	No				
Household panel data without shocks	**1995–2003** (962)?	?	No	No	No
Household stratified sample survey data	NLSS 1995 (3373) 2003 (3912)	**DevInfo/ Iran Central Bank** ?	HIES **1992 (~)** **1996 (~)** **2002 (~ 15000)** 2006 (~ 18000)	NSS 1992 (367) **1994 (3187)** **2000 (2695)** 2002 (519) 2004 (341) **2005 (3000+)**	NSS 1992 1994 2000 2002 2004 2005

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