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Socioeconomic Resilience

Multi-Hazard Estimates in 117 Countries

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Abstract

This paper presents a model to assess the socioeconomic resilience to natural disasters of an economy, defined as its capacity to mitigate the impact of disaster-related asset losses on welfare. The paper proposes a tool to help decision makers identify the most promising policy options to reduce welfare losses from natural disasters. Applied to riverine and storm surge floods, earthquakes, windstorms, and tsunamis in 117 countries, the model provides estimates of country-level socioeconomic resilience. Because hazards disproportionally affect poor people, each $1 of global natural disaster-related asset loss is equivalent to a $1.6 reduction in the affected country's national income, on average. The model also assesses policy levers to reduce welfare losses in each country. It shows that considering asset losses is insufficient to assess disaster risk management policies. The same reduction in asset losses results in different welfare gains depending on who (especially poor or nonpoor households) benefits. And some policies, such as adaptive social protection, do not reduce asset losses, but still reduce welfare losses. Post-disaster transfers bring an estimated benefit of at least $1.30 per dollar disbursed in the 117 countries studied, and their efficiency is not very sensitive to targeting errors.

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Socioeconomic Resilience: Multi-Hazard Estimates in 117 Countries

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1. Introduction

The most immediate consequences of natural hazards are the fatalities and casualties, and the first priority of disaster risk management is to save lives. But natural disasters also have economic consequences, which affect wellbeing and need to be accounted for and managed (Cavallo and Noy, 2011; Rose, 2009; Skoufias, 2003). These economic consequences and wellbeing losses depend on the value of what is lost or damaged, and on many other factors, including how long it takes to rebuild, how asset losses translate into income losses, and how coping mechanisms and ex-post support (from insurance to social protection) protect the victims and help smooth consumption losses (Carter et al., 2007; Le De et al., 2013). In addition, wellbeing losses are larger when losses are concentrated, especially when concentrated on poor people – as is often the case (Hallegatte et al., 2016a). Disasters can also have irreversible and long-term health consequences, particularly on children (Dercon, 2004; Maccini and Yang, 2009).

Many policies can minimize wellbeing losses and protect the population: from building dikes and restoring mangroves to better land-use planning and early warning, to evacuation, insurance and social safety nets. Risk management policies are best designed as holistic strategies that combine many of these levers (World Bank, 2013).

Designing such a consistent policy package is challenging; here we build on Hallegatte et al. (2016b) and propose an approach and a model to support this process. In this work-in-progress, we combine data on natural hazards, population and asset location, asset vulnerability, and socioeconomic characteristics and combine insights from natural and social sciences to assess how natural disasters affect wellbeing, measured using a *social welfare function* (*welfare* is the metric used by economists to measure wellbeing). We first present the model, and the global data used to calibrate it. We then use the model to define and assess the socioeconomic resilience of 117 countries to natural disasters, identify policy priorities to reduce the impact of disasters on wellbeing, with a focus on adaptive social protection, and help design holistic risk management strategies tailored to each country. The model and the data are available online.[1]

We propose a new quantifiable definition of *socioeconomic resilience*, the ratio of *asset* losses to *welfare* losses[2]:

$$\text{Socioeconomic resilience} = \frac{\text{Asset losses}}{\text{Welfare losses}}$$

With this definition, socioeconomic resilience can be considered as a driver of the risk to wellbeing – measured through the expected welfare losses due to natural disasters – along with the three usual drivers, hazard (the probability an event occurs), exposure (the population and assets located in the affected area) and asset vulnerability (the fraction of asset value lost when affected by a flood):

[1] The code and data set are available at github.com/adrivsh/resilience_indicator_public/

[2] This definition combines the notions of macroeconomic and microeconomic resilience previously proposed by Hallegatte (2014).

$$\text{Risk to wellbeing} = \frac{\text{Expected asset losses}}{\text{Socioeconomic resilience}} = \frac{(\text{Hazard}) \cdot (\text{Exposure}) \cdot (\text{Asset vulnerability})}{\text{Socioeconomic resilience}}$$

Socioeconomic resilience (*resilience* for short in this paper) measures the ability of an economy to minimize the impact of asset losses on wellbeing and is one part of the ability to *resist*, *absorb*, *accommodate* and *recover in a timely and efficient manner* to asset losses (the qualitative definition of resilience from the United Nations). In an idealized case of perfect risk-sharing across the population, no irreversible impacts on human capital, and no pre-existing inequality, welfare losses are equal to asset losses. Socioeconomic resilience at 50% means that welfare losses are twice as large as asset losses, and could be reduced by half if inequality disappeared, losses were perfectly shared, and irreversible impacts were avoided.

We develop and use a model to estimate expected asset losses and expected welfare losses, and quantify socioeconomic resilience in 117 countries. The model builds on Hallegatte et al. (2016b), which only considered river floods and 90 countries. Here we add new countries thanks to new socioeconomic data, and we introduce additional hazards – coastal floods and storm surge, windstorm, earthquakes, and tsunamis – using the risk assessment provided in the Global Assessment Report (UN-ISDR 2015). We also simplify the model – focusing on the factors that were found to have most influence on our previous assessment and disregarding other factors – and improve our modeling of insurance and social protection.

Like all models, ours is incomplete and our assessment provides a partial view of resilience. For instance, we do not include many non-economic components such as the link between disasters, conflicts, and state fragility. Nevertheless, our quantification informs on the ability of economies to deal with natural disasters and on the prioritization of policy options to improve resilience.

We find that some policy options can reduce welfare losses by increasing socioeconomic resilience, from an unchanged amount of asset losses. Adaptive social protection is a particularly promising one. In all countries, every dollar spent on post-disaster support yields at least $1.30 of increased welfare. In 11 countries—Angola, Bolivia, Botswana, Brazil, Central African Republic, Colombia, Honduras, Lesotho, Panama, South Africa, and Zambia—every $1 spent on post-disaster transfers yields well-being benefits of more than $4. Our simulations also suggest that uniform transfers may be preferable. Indeed, wealthier households may receive most of the available resources if transfers are proportional to losses, leaving little for those most in need. There is thus a complementarity between premium-funded insurance programs for wealthier households who can afford the transaction costs, and publicly-funded adaptive social protection for the poorer.

Resilience gains from poverty reduction can even offset increased asset losses. Increasing by 10 percentage points the share of income of the bottom 20 percent in the 117 countries would increase asset losses by 1%, since more wealth would be at risk. But it would also reduce the impact of income losses on wellbeing, increasing resilience by 0.6% on average, and ultimately reduce welfare losses by $500 million per year.

These findings suggest that the common practice of tracking only asset losses (IPCC, 2012) may give an overly pessimistic view of progress made by countries in terms of disaster risk management; and that

taking into account distributional impacts and ex-post support mechanisms can better inform policy recommendations.

We also use the model to assess a set of policy levers in 117 countries, according to their country-specific efficacy to reduce risk to welfare through its four drivers. We display this information using country-level policy cards, which report in each country how improving each sub-indicator would impact risk, resilience and therefore asset and welfare losses for that country. In contrast, existing indicators for resilience, risk, or vulnerability attribute the same weights to each sub-indicator in every country (we compare our indicator with other existing indicators in the appendix). Our approach provides an innovative framework to assess in a consistent manner the benefits from hard measures (e.g., dikes, building norms) and softer options (e.g., post-disaster support, financial inclusion). These assessments provide an input to the cost-benefit analysis of these options and can be used to support a dialogue on the priority actions for disaster risk management in different countries, regions or cities.

2. From asset losses to welfare losses

2.1. Reconstruction dynamics

This section explains our model. The first step of the assessment is to compute how asset losses translate into discounted consumption losses.

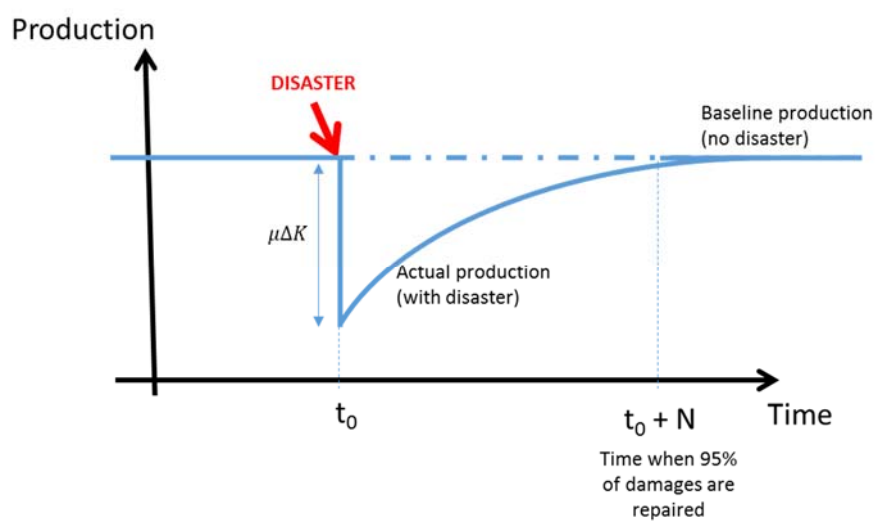


Figure 1 Schematic view of the economic output dynamics. The variable μ is the average productivity of capital and N is the reconstruction period duration (until 95% of damages are repaired).

According to Hallegatte and Vogt-Schilb (2016), if 95% of reconstruction is done exponentially over N years, the discount factor is ρ and the average productivity of capital is μ, then the present value of consumption losses $\widetilde{\Delta C}$ is linked to asset losses at the moment of the disaster ΔK by a factor Γ :

$$\widetilde{\Delta C} = \frac{\mu + {}^{3}/_{N}}{\rho + {}^{3}/_{N}} \Delta K = \Gamma \Delta K \qquad \textbf{Equation 1}$$

The relation involves average, not marginal productivity of capital, because natural disasters do not destroy the least productive assets first, but affect random sectors and random portions of the existing capital (Hallegatte and Vogt-Schilb 2016). Note that if the productivity of the affected capital was equal to the marginal productivity of capital, that is $\mu = \rho$, then the loss of consumption would simply be equal to the loss of capital (and would thus be independent of the reconstruction duration).

Then, to estimate the welfare impact of a macroeconomic loss in consumption, it is necessary to account for the distributional impacts of the disaster, that is whether it impacts poor or nonpoor people, and for the ability of the population to cope with the shock. Our framework is flexible regarding the definitions of "poor" and "non-poor."[3] In particular, one can decide to focus on extreme poverty by defining the poor following national or international poverty lines; through a Multidimensional Poverty Index; using a given fraction of the population (e.g., the bottom 20 or 40% of the income distribution); or using a broader definition of poor people that is relevant for disaster analysis (e.g., the population with no access to financial instruments, or the population that is "vulnerable" to falling back into poverty[4]). In what follows, we define the poor as the people in the bottom 20% of the consumption distribution. All the calculations that are proposed in this section are nonetheless possible in a more complex framework with more than two categories.

2.2. Distribution of asset and consumption losses

The distribution of losses from a disaster depends on poverty, assets used, affected individuals and capital, and consumption losses, as each section of the framework below describes.

2.2.1. Income categories

In each country, there are n individuals, partitioned in n_p poor people and n_r non-poor people. We call poverty headcount p_h the share of poor people in the economy:

$$p_h = {}^{n_p}/_{n} \qquad \textbf{Equation 2}$$

The aggregate national consumption, income and assets are noted C, $Y$and K. The variables c_p, c_r, and c are the per capita consumption of poor, nonpoor and average individuals, respectively.

2.2.2. Affected and non-affected people

To calculate the welfare impact of the disaster, we start by identifying the number of poor and non-poor people that are directly affected by the shock, and the number of those that are not directly affected (but are affected by indirect impacts).

[3] However, since the main difference between poor and non-poor will be the marginal utility of income, monetary definitions of poverty appear more appropriate than non-monetary definitions, in this very context.
[4] See a discussion on the World Bank website: http://go.worldbank.org/R048B34JF0.

The disaster affects a proportion$f^a = n^a/n$, of the population, where n^a is the number of directly affected persons. The variables n_p^a and n_r^a represent the number of poor and non-poor people in the affected area. The fraction of poor people affected is $f_p^a = n_p^a/n_p$ and the fraction of non-poor people affected is $f_r^a = n_r^a/n_r$.

We sometimes also use the *poverty-exposure bias for population*, given by $PE = \frac{f_p^a}{f^a} - 1$. The parameter PE measures how the share of the poor in the affected area compares to the share of the poor in the entire country. If *PE* is larger than zero, poor people are more affected than the rest of the population, the disaster is biased and affects the poor disproportionally. If the disaster affects only the poor, then PE reaches a maximum of n/n_p-1; if the disaster affects only the non-poor, if reaches a minimum of -1.

These parameters allow counting the population in each category (**Table 1**).

	Directly affected	Non directly affected
Poor	$n_p^a = p_h f_p^a n$	$n_p^n = p_h(1 - f_p^a)n$
Non-poor	$n_r^a = (1 - p_h) f_r^a n$	$n_r^n = (1 - p_h)(1 - f_r^a)n$

Table 1: Estimating exposure to a disaster for four categories, based on poverty status and exposure of the poor and non-poor people.

2.2.3. Labor income and transfers

Consumption comes from two income sources: labor income–assumed generated locally and thus vulnerable to local asset losses—and transfers from social protection, capital income, and remittances – assumed perfectly shared at the national level and thus vulnerable to losses at the national level.

$$c_i = \mu k_i(1 - \tau) + t_i \qquad \textbf{Equation 3}$$

Where c_i represents consumption, μ is the average productivity of capital, k_i is the capital *used* by the poor ($i = p$) or the non-poor ($i = r$), τ is the share of production that is diverted to fund transfers, and t_i are transfers received. The assets "used" by an individual are the assets that participate in generating his or her income. They include the assets people own (e.g. a cow, a sewing machine or a saving financial asset); the infrastructure the individual uses to access transport, water, and energy services (e.g., roads); the assets owned by others but that the individual uses to work (e.g., factory equipment); and the assets that produce the resources that are redistributed through social protection. The distinction matters because many poor people do not own many physical assets, but may lose income because they use assets that belong to other individuals or to the government.

The other source of income, t_i, is the transfers, i.e. income diversified at the national level. It comes from social transfers, remittances, or capital that is invested in a diversified manner (e.g., through a bank saving account). Note that we do not represent explicitly the income generated outside the affected country, such as international investments and foreign remittances for simplicity.

We define τ as an effective tax rate on capital, which captures average income diversification in the economy. It is the share of local production that benefits the rest of the economy. The budget constraint for transfers reflects the fact that all transfers must come from such diversion:

$$\Sigma_i t_i = \Sigma_i \mu \tau k_i \qquad \textbf{Equation 4}$$

In a traditional economy without transfers or social protection (or with only local community-level transfers) and little international openness, $\tau = 0$; in a modern economy in which transfers and capital gain play a larger role, τ is much higher.

We also define γ_i as the share of total transfers that go to category i, that is

$$t_i = \gamma_i \Sigma_i \mu \tau k_i \quad \textbf{Equation 5}$$

2.2.4. Asset and consumption losses

We define parameters V_p and V_r as the physical vulnerability of affected capital for poor and non-poor people, respectively. It is defined as the fraction of the affected capital that is lost because of the disaster. The assets that generate the income of poor people are generally more vulnerable than the assets used by non-poor people (e.g., lower quality houses that can be completely wiped out by wind), $V_p > V_r$.

From these capital losses, taking into account reconstruction dynamics (previous section, assuming uniform reconstruction duration) gives the *net present value* of consumption losses by multiplying by Γ.[5] Taking into account the effect through income diversification one gets:

$$\widetilde{\Delta c}_{\mathrm{i}} = \Gamma[(1-\tau)\Delta k_i + \tau \gamma_i \Sigma_i \Delta k_i] \qquad \textbf{Equation 6}$$

2.2.5. Insurance, and scale-up of remittances and social protection

To assess the ex-post situation and the final impact on people's welfare, we need to account for the possibility that the affected population relies on increased public and private transfers, as well as withdrawal from saving accounts to smooth the impact of asset losses on welfare losses. Here, we focus on the willingness and ability of the government to scale up social transfers to compensate for asset losses, and we compare that to premium-financed private insurance.

One issue with post-disaster support is imperfect targeting. Ex-post support may suffer from inclusion errors, where nonaffected people are wrongly provided support, and exclusion errors, where affected people do not receive the aid they should. To track this, we classify the population in 8 categories, using the 4 previous categories, plus whether they receive support. The number in each category is given by the following table:

[5] All values noted with a tilde (like $\tilde{x}$) are for the net present value of the future flux, not the instantaneous value at time t.

	Directly affected		Non directly affected	
	Support received	Support not received	Support received	Support not received
Poor	$n_p^a\,(1-\mathrm{e_e})$	$n_p^a \mathrm{e_e}$	$n_p^n \mathrm{e_i}$	$n_p^n(1-\mathrm{e_i})$
Non-poor	$n_r^a(1-\mathrm{e_e})$	$n_r^a \mathrm{e_e}$	$n_r^n \mathrm{e_i}$	$n_r^n(1-\mathrm{e_i})$

Where the exclusion error parameter is $\mathrm{e_e}$ and $\mathrm{e_i}$ is the inclusion error parameter.

Two other issues are the amount of support distributed, and how the support is funded. In general, for each category of household, total consumption losses after post-disaster support are given by

$$\widetilde{\Delta c}_{\mathrm{i}} = \Gamma[(1-\tau)\Delta k_i + \tau\gamma_i \Sigma_i \Delta k_i] - h_i + f_i \quad \textbf{Equation 7}$$

Where h_i is the support received per capita, and f_i is the amount paid per capita to fund the support ($\Sigma_i f_i = \Sigma_i h_i$). **Figure 2** illustrates the previous equation.

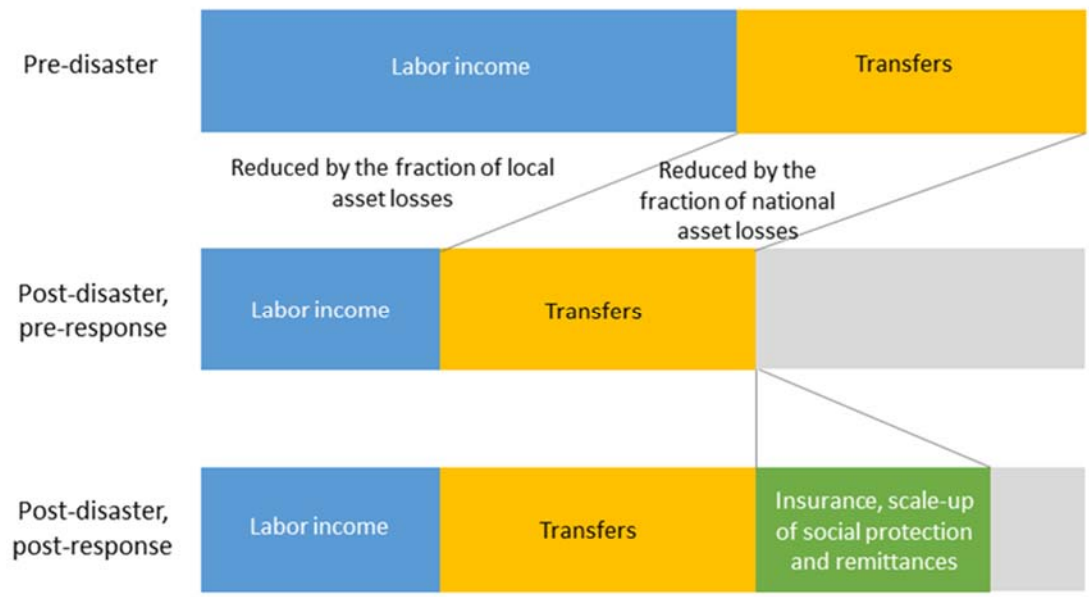


Figure 2 Income of one category (poor or non-poor) before the disaster, after the disaster but before the response to the disaster, and after the disaster and the response.

2.3. Welfare impacts from consumption losses

We assume the welfare in the affected country is given by:

$$W = n_p w(\widetilde{c_p}) + n_r w(\widetilde{c_r}) \qquad \textbf{Equation 8}$$

The function w is a "welfare function" that links the *net present value of* consumption ($\widetilde{c_p}$ and $\widetilde{c_r}$) with individual welfare.[6] Using the net present values of consumption to assess welfare is a simplification, which is acceptable if individuals can smooth the shock over time and if the shock remains relatively limited compared with consumption. The change in social welfare is the sum of the change in welfare for the 8 categories of individuals.

After the disaster, the welfare is given by:

$$W = n_p w(\widetilde{c_p} - \widetilde{\Delta c_p}) + n_r w(\widetilde{c_r} - \widetilde{\Delta c_r}) \qquad \textbf{Equation 9}$$

The net present value of consumption in the baseline – without disaster – is given by the discounted sum of current consumption, assumed constant in the future:

$$\tilde{c} = \frac{1}{\rho} c \qquad \textbf{Equation 10}$$

Further, we use a constant relative risk aversion welfare function:

$$w(\tilde{c}) = \frac{\tilde{c}^{1-\eta} - 1}{1-\eta} \qquad \textbf{Equation 11}$$

Where η measures both risk aversion and aversion to inequality, and is the inverse of the elasticity of the marginal utility of consumption. Here, the parameter η is the degree of aversion to inequality in consumption, which represents the diminishing marginal utility of consumption (i.e., the lesser importance of consumption as one gets richer). Indeed, differences in pre-disaster consumption levels translate into differences in the marginal utility of consumption: consumption losses of poorer people will matter more than those of richer people. These differences can be interpreted as a *distributional weight*, classically used to compare losses and benefits that affect individuals of different incomes and wealth (Fleurbaey and Hammond 2004).

With η equal to one, a 10-percent consumption loss for poor people "weights" as much as a 10-percent consumption loss for non-poor people, even though the latter is much larger in monetary terms. Higher values of η give more weight to what happens to poor people, vs. non-poor people. In this analysis, we take $\eta = 1.5$, which is consistent with a focus on poverty (a value larger than one is consistent with the preference for a progressive tax system in which richer individuals pay a larger share of their income). Since there are disagreements on the appropriate value for η, we propose in Hallegatte et al. (2016b) a sensitivity analysis on this parameter.

[6] The net present value of future consumption can be understood as the wealth of the individual, i.e. the value of all his or her assets, including human capital.

3. Data and calibration

This section explores how we assess socioeconomic resilience at the national level. To ensure transparency and replicability – and to allow the reader to test various assumptions – the code that calculates the resilience indicators based on various data sets and that creates all figures presented below is available online.

3.1. Poverty definition

We need first to describe inequality and poverty levels in the affected region. We define the poor as the individuals in the bottom quintile in terms of consumption or income. Therefore, the parameter p_h is equal to 20%. To estimate c_p and c_r, we use the World Development Indicators database, which provides the income share of the bottom 20%. Figure 3 shows the result, highlighting the large variability – and lack of correlation – between inequality and national income level.

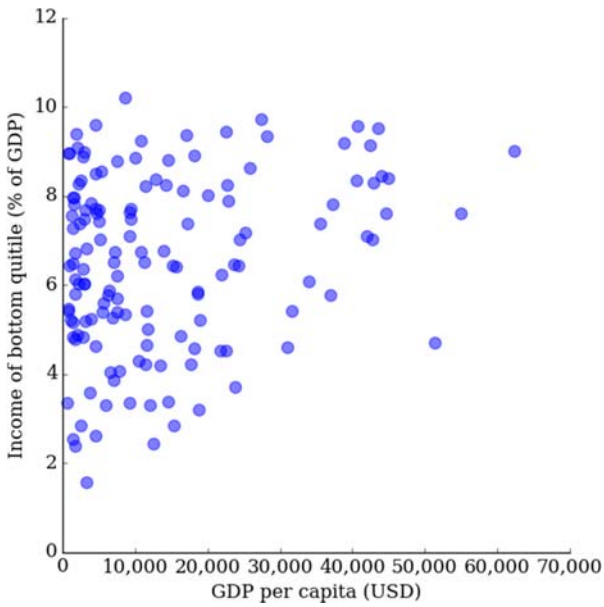


Figure 3. Income share of the bottom 20 percent, in percent of GDP, as a function of GDP.

3.2. Asset vulnerability

A few household surveys have examined the percentage of asset losses (that is, asset vulnerability) for households at different income levels. Several caveats are needed before interpreting the above estimates of asset vulnerabilities. First, each study has a different definition of "poor" and "non-poor", which does not always fit our 20/80 categorization. Second, vulnerability depends on the type of hazard and context in which it occurs. Even within the same country (e.g. Bangladesh in the table below), measures vary greatly. Third, the methods through which vulnerability estimates are captured also differ in each study (hence the range of vulnerabilities varies widely across studies).

Country	Hazard	Year	Vp	Vr	Source
Bangladesh	Flood	2005	42%	17%	Brouwer et al. (2007)
Bangladesh	Flood/cyclone	2009	74%	45%	Rabbani et al. (2013)
Bangladesh	Flood/cyclone	2009	10%	6%	Akter & Mallick (2013)
Honduras	Hurricane	2001	31%	11%	Carter et al. (2007)

Table 2: Estimates of the poverty vulnerability bias from prior studies.

Moreover, these studies only look at the capital owned by households, not at the capital they depend upon to generate their income. This includes also infrastructure (e.g., roads, electricity network) and productive capital (e.g., factories, supply chains). Here, we assume that the vulnerability of housing capital is comparable to the vulnerability of the rest of the capital – for instance, if poor people's buildings are 20 percent more vulnerable, then we assume that the capital they use to generate an income is also 20 percent more vulnerable.

3.2.1. Vulnerability estimates based on housing data

In this national-level analysis, and consistent with our focus on the socioeconomic drivers of resilience, we use a very simple methodology. We use the Global Building Inventory database from PAGER, by USGS, which provides a distribution of building types (buildings only, not contents) within countries across the world (USGS 2015). This typology has been developed to assess vulnerability to earthquakes but here we use it for all hazards.

There are 106 building types in PAGER, which we aggregate into three categories, by vulnerability level (see Appendix). Then, we apply simple depth-damage functions for each of the three aggregated categories, inspired Hallegatte et al. (2013). The most vulnerable buildings are aggregated into one "fragile" category, and we assume that 70 percent of the building value is lost if a building in this category is affected. In addition, we have a "median" and a "robust" category, for which losses are equal to 30 and 10 percent. The PAGER data do not tell who is living in buildings of different categories. Here, we assume that the poorest live in the most vulnerable buildings; a very reasonable assumption in most cases. These loss ratios, developed for buildings, are also applied to the rest of the capital, including infrastructure and factories. The underlying assumption is that if individuals are living in fragile homes – for instance a mud wall house – they are also serviced by fragile infrastructure and work in fragile factories and buildings.

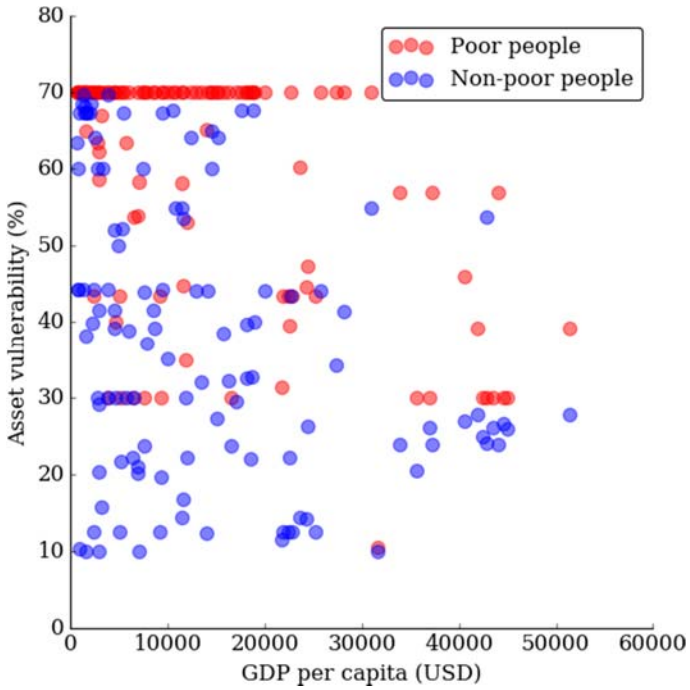


Figure 4: Asset vulnerability of poor and non-poor people against GDP per capita.

The result of this analysis is shown in **Figure 4**, with the asset vulnerability – the fraction of assets that is lost in case of a natural disaster, for the poor and the non-poor, in the 117 countries, and as a function of the GDP per capita. It shows that in most low-income countries, all poor people are living in fragile buildings, while in rich countries even the poor have less vulnerable housing. The situation is very diverse across countries for the non-poor. But overall, housing vulnerability is decreasing with income, as is probably capital vulnerability in general. Moreover, dispersion is grossly decreasing when income increases, meaning that on average asset vulnerability bias decreases with income.

3.2.2. Vulnerability and early warning systems

Capital losses can be reduced significantly thanks to early warning systems (Hallegatte 2012)**.** For instance, (Kreibich et al., 2005) report on the Elbe and Danube floods in 2002. They show that 31% of the population of flooded areas implemented preventive measures. These measures include moving goods to the second floor of buildings (applied by more than 50% of the inhabitants who implemented prevention measures), moving vehicles outside the flood zone (more than 40%), protecting important documents and valuables (more than 30%), disconnecting electricity and gas supplies and unplugging electric appliances (more than 25%) and installation of water pumps (between 2 and 10%).

In our national indicator, we include the role of early warning system using data reported in the context of the Hyogo Framework for Action[7] (UN-ISDR, 2015a). The priority for action #2 ("Identify, assess and monitor disaster risks and enhance early warning") includes an indicator (P2-C3) related to "Early warning

[7] http://www.unisdr.org/we/coordinate/hfa.

systems are in place for all major hazards, with outreach to communities" with a score between 0 and 5. We attribute a score equal to zero to countries that did not contribute to the HFA monitoring system.

We assume that individuals with access to early warning can reduce capital losses by $\pi = 20\%$, and that the fraction of the population with access depends linearly on the HFA indicator: 0% for a score of 0, 20% for a score of 1, up to 100% for a score equal to 5. So actual vulnerability is equal to:

$$V_a = V\left(1 - \frac{HFA_{P2C3}}{5}\pi\right)$$

Equation 12

Where HFA_P2C3 is the HFA indicator related to "Early warning systems are in place for all major hazards, with outreach to communities."

3.3. Exposure

3.3.1. Computing population and asset exposure by hazard and return period

The exposure of the population and assets to natural disasters is derived from UN estimates of expected asset losses and our estimates of asset vulnerability. The Global Assessment Report (UN-ISDR 2015), referred to as the GAR report, provides for each country and hazard (riverine floods, windstorms, storm surge, earthquakes and tsunamis) asset losses per return periods (from 20 to 1,500 years) as well as average annual losses (AAL). We first estimate frequent asset losses per country and hazard (for the one year return period event) such that averaging events over return period matches average annual losses provided by the GAR.

Then, we derive the exposure per country, hazard and return period that is consistent with these asset losses and the vulnerability derived before, that is:

$$\Delta K = f_a V_a \qquad \textbf{Equation 13}$$

Where V_a is asset vulnerability as computed in the previous section, ΔK is the value reported in the GAR, and f_a is the fraction of assets affected (that is the exposure) we solve for.

3.3.2. Summing over return periods

To aggregate asset and welfare losses, taking into account that exposure depends on the return period, we proceed as follows. First, we assume that no other parameter than total exposure depends on the return period (the model structure allows to make arbitrary parameters depend on the return period). Second, we compute asset losses and welfare losses in each country for each return period independently. And third, we aggregate the resulting asset and welfare losses, weighting them with the probability of each event occurring.

3.3.3. Exposure bias

For riverine and coastal floods, we specify a different exposure for poor and nonpoor people. To calibrate the exposure bias, we use the estimates published in (Hallegatte et al. 2017). This World Bank study

overlays flood maps from the GLOFRIS global model and poverty maps from the World Bank. For countries where this study does not provide data, we use an older, similar study by (Winsemius et al. 2015). This other World Bank study overlays the same GLOFRIS flood maps as above with geo-localized household surveys (using the Demographic and Health Surveys[8]) to assess the exposure of poor people to river floods relative to the exposure of non-poor people.

Where neither study provides data, we use the average for countries which do have data weighted by their population (the average is 8%). This average is conservative, when compared with the few estimations found in published case studies (**Table 3**).

Country	Hazard	Year	Poor	Nonpoor	Bias	Source
Bangladesh	Flood/cyclone	2009	25%	14%	56%	Akter & Mallick (2013)
Mumbai	Flood	2010	41%	24%	71%	Patankar and Patwardhan
Kenya	Flood	2012	99%	96%	1%	Opondo(2013)
Guyana	Flood	1997	40%	28%	18%	Pelling (1997)
Vietnam	Flood	2011	38%	29%	17%	Nguyen and James (2013)

Table 3: Exposure of poor and nonpoor people in selected case studies

We assume there is no exposure bias for other hazards, due to the large scale of these events. This is a simplification considering for instance that local soil characteristics have an impact on earthquake vulnerability.

3.4. Macroeconomic characteristics

First, we translate the population exposure (separated into poor and non-poor people) into asset exposures for the two categories. To do so, we assume that the capital used by an individual to generate his or her labor income is the ratio of this labor income by the average capital productivity. Since we have the labor income of the poor and non-poor, we can translate those into the exposed non-diversified capital of the poor and non-poor. We calculate the average capital productivity as output-side GDP divided by total reproducible capital within a country, both variables from Penn World Tables.

Figure 5 shows the average productivity of capital against income level. In spite of a large variance, high income countries tend to have more capital and as a result their capital is on average less productive. As shown in Hallegatte and Vogt-Schilb (2016), countries with a high average productivity of capital have in general less to spend (in proportion of their income) in reconstruction, and this increases their resilience. This effect mitigates the effect of all other drivers, which tend to make richer countries more resilient than poorer ones.

[8] http://www.dhsprogram.com/.

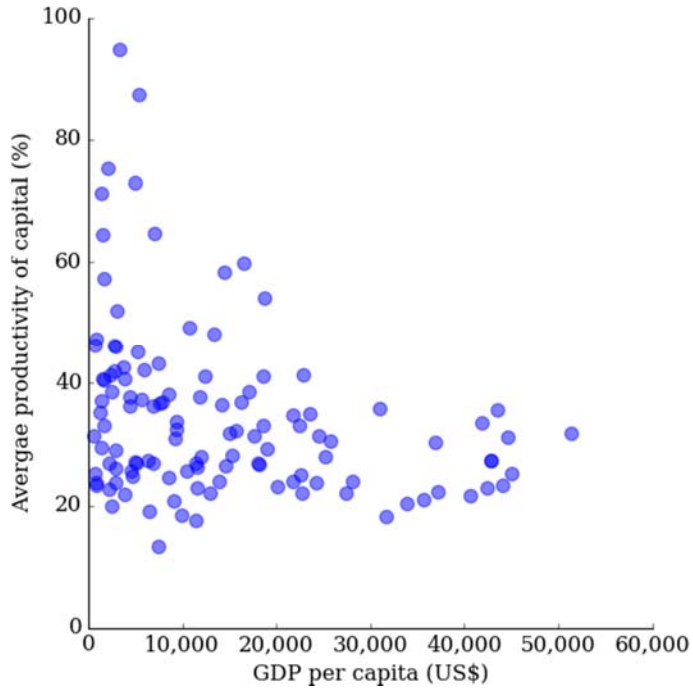


Figure 5: The average productivity of capital, for the 117 countries.

We assume that reconstruction takes place in three years, regardless of the extent of the event.[9]

3.5. Asset diversification

To estimate the fraction of income of the poor and non-poor that comes from social protection and transfers, we calibrate t_i using the "average per capita transfer from all social protection and labor (for beneficiaries)" and the coverage in each quintile from the ASPIRE database[10] :

$$\lambda_p = \frac{Cov(bottom\ 20\%)\ B_{pc}(\text{bottom } 20\%)}{c_p}$$

Equation 14

$$\lambda_r = \frac{Cov(top\ 80\%)\ B_{pc}(\text{top } 80\%)}{c_r}$$

Equation 15

Where B_{pc} is the share of income sources which comes from social protection and remittances among people receive a transfer, and Cov is the coverage, that is the fraction of people receiving a transfer in

[9] More work would be required to identify the drivers of the reconstruction duration. In previous work, it was suggested that the reconstruction duration is dependent on the size of the construction sector (which supports most of the reconstruction effort in many cases) and on the ability to mobilize resources for the reconstruction.

[10] The Atlas of Social Protection: Indicators of Resilience and Equity (ASPIRE). http://datatopics.worldbank.org/aspire/

that quintile. Poor and non-poor correspond to the bottom 20% and the top 80% respectively. ASPIRE at present does not cover developed countries, so we use data from the US Consumer Expenditure Survey (CES, 2015), Canadian National Household Survey (CNHS, 2015), Australian Household Wealth and Wealth Distribution Survey (AWWDS, 2015), and European Union Survey of Income and Living Conditions (EU-SILC, 2015).

ASPIRE does not cover all countries in the world. To expand the set of countries in this study, we proceed as follows. First, we estimate an econometric model that explains the share of income from transfers, for poor and nonpoor people in each country by the share of GDP spent on social protection at the national level (from the International Labour Organization), an indicator of government effectiveness (from the Worldwide Governance Indicators), and whether the country used to be in the Soviet Union. (Other explanatory variables we tested include World Bank income category of the country, region, and GINI coefficient, but they turn out to have no explanatory power.) This provides an estimate of income from transfers in 26 additional countries (from 98 using only ASPIRE data).

Diversification also comes from financial inclusion. We use the fraction of the population with savings at a financial institution, from the Global Financial Inclusion Database (FINDEX, 2015). The Findex database provides these values for the bottom 40% and for the top 60%, which we use for poor and nonpoor people respectively. We assume that the fraction of income that is diversified increases by 10% for people who have bank accounts.

Figure 6 shows the diversification of income thanks to remittances and social protection for poor and non-poor people as a function of GDP per capita. It shows that generally, poor people receive a large share of their income from transfers (which sounds logical but is not the case in all countries). Here, we see that most countries below $10,000 GDP per capita have limited social protection systems, but there are exceptions, and a large variability for countries above this level. The figure also show the fraction of poor and nonpoor people with bank accounts, showing that financial inclusion is still very low in low income countries.

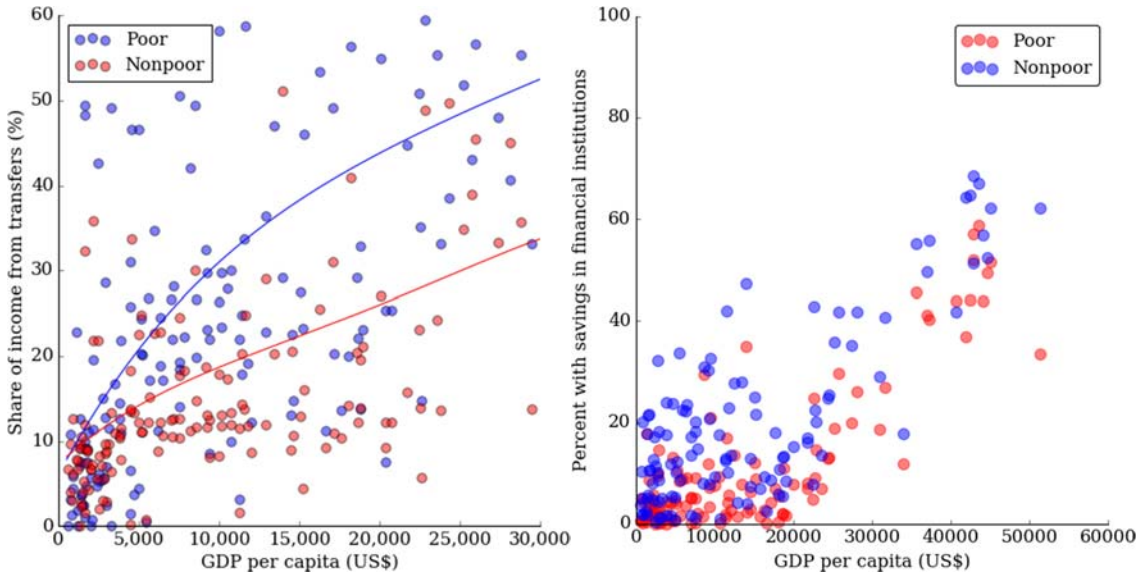


Figure 6: Diversification of income for poor and non-poor households.

3.6. Sharing losses across individuals – Insurance and scalable social protection

Insurance, scalable social protection and social networks may transfer some of the losses from the affected to the non-affected and from the poor to the non-poor. It is the case if lost income is replaced by cash transfers (or cash-for-work programs) for the most affected, paid by the rest of the population, or in the presence of subsidized insurance.

In many countries, assuming that insurance is not present is an acceptable assumption. There are some exceptions, especially in countries where flood insurance is subsidized (e.g., the US) or subsidized and mandatory (e.g., France). In the absence of a global database of insurance coverage, we assume that insurance is negligible.

In every country, the government or local authorities intervene to insure implicitly the population. In a first simple analysis, we assume that the government would like to issue a lump sum payment to people affected, covering 80% of average losses of poor people. But doing so may be impossible, for two main reasons, which limit this risk sharing mechanism:

- The social protection system may not be designed to respond to natural disasters by increasing the volume of support and targeting the affected households (Kuriakose et al. 2013; World Bank 2013). In some cases, specific changes have been introduced to social protection systems, to make sure they can accommodate the needs from disasters, such as the Productive Safety Net Program in Ethiopia (World Bank, 2013b, Spotlight 2). To account for these elements, we use the HFA reporting system, in the priority for actions #4 and #5, with three indicators that describe how a country is prepared to act in the post-disaster phase.[11] We take the average of these three

[11] The three indicators are:

- P4C2: Do social safety nets exist to increase the resilience of risk prone households and communities?

indicators (divided by 5 to remain between zero and one) as an indicator q_s of the ability to scale up support to the affected population after the disaster: $q_s = (P4C2 + P5C2 + P4C5)/3/5$.

- The additional cost may be too high for the country and cannot be financed, unless reserves or special funds have been created, or emergency borrowing can take place. Melecky and Raddatz (2011) find that government deficits increase by 25% after a climatic disaster, due to increased expenditure (15%) and reduced revenues (10%). They also find that the increase in expenditure and deficit does not depend on pre-existing debt (one explanation proposed by the authors is that countries with higher debt also have higher borrowing capacity). This is why we do not account for the debt-to-GDP ratio in the ability of countries to support affected population. Rather, we proxy the ability of a country to borrow with sovereign credit rating, using the average (long-term) rating of from three agencies: S&P, Moody's and Fitch. Before taking the average, we convert alphabetical ratings to numerical values linearly (assigning default a 0 score). To account for Sovereign Disaster Risk Financing (SDRF) instruments such as contingency credit lines (Cat-DDO), Cat-Bonds, Sovereign insurance or dedicated rainy day funds, we use the third indicator of the HFA priority for action #5 ("Financial reserves and contingency mechanisms are in place to enable effective response and recovery when required"). We define an indicator for the ability to finance the scale-up, defined as $q_f = \frac{1}{2}(Rating + P5C3/5)$.

Specifically, we assume the ability to scale up to affect inclusion and exclusion errors as follows:

$$e_i = \frac{(1 - q_s)}{2} \frac{f_a}{(1 - f_a)}$$

$$e_e = \frac{(1-q_s)}{2} \quad \textbf{Equation 16}$$

So that if the country has 100% of ability to scale up, both errors are null, and if it has no ability at all, then half the aid is given to non-affected instead of affected people.

Concerning financing of the aid, we assume that if a country rates 100% in its ability to borrow, then the maximum spending in post disaster support is 5% of GDP. Otherwise, that maximum spending decreases proportionally to $(1 - q_f)$. Actual payments h_i then are scaled down linearly to meet this maximum budget.

Figure 7 shows the ability to scale up and borrow across the sample.

- P5C2: Disaster preparedness plans and contingency plans are in place at all administrative levels, and regular training drills and rehearsals are held to test and develop disaster response programs.
- P4C5: Disaster risk reduction measures are integrated into post-disaster recovery and rehabilitation processes.

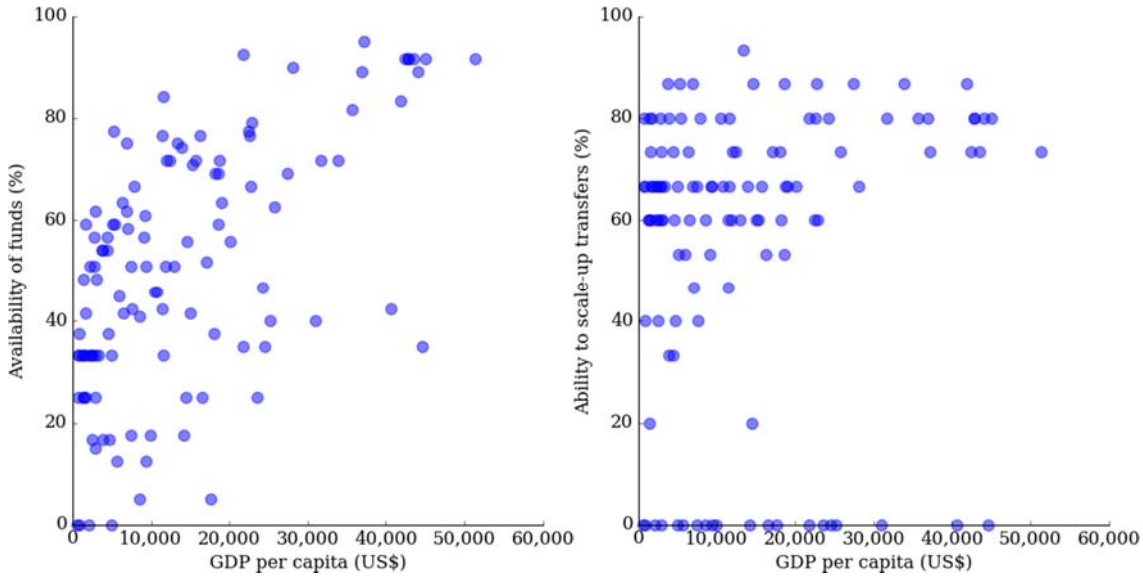


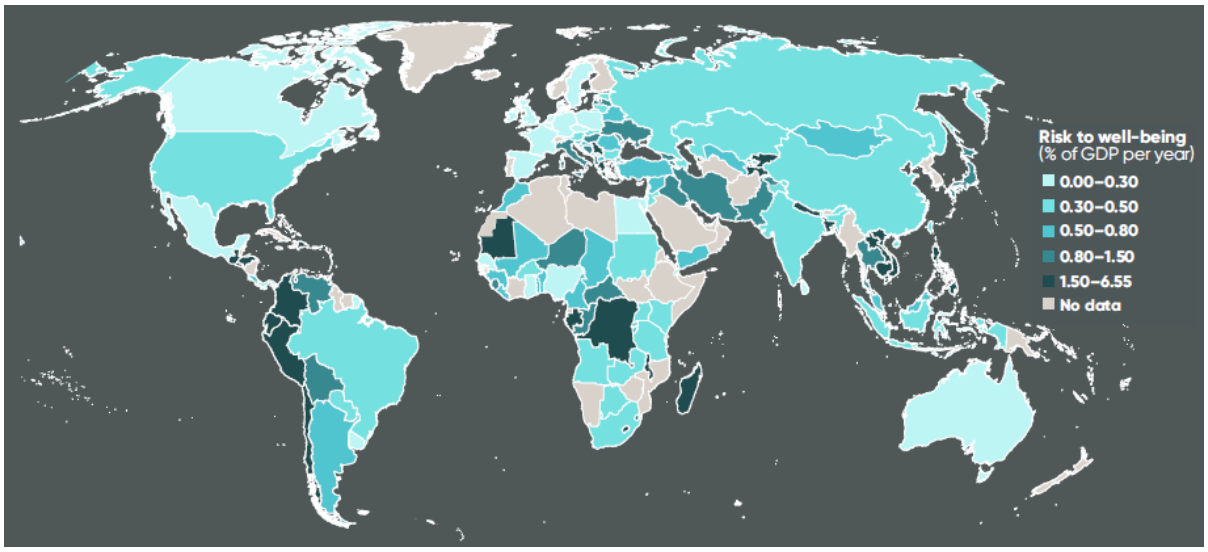
Figure 7: Ability of the government to mobilize fund and increase social spending in the aftermath of a disaster

We then run several alternative simulations to understand the importance of targeting errors, funding constraints, and disbursement calibration. These simulations and their results are presented below.

4. The socioeconomic resilience to natural disasters in 117 countries

4.1. A global look at risk and socioeconomic resilience

The resulting risks to welfare are presented in Map 1 and Figure 8. Risk to wellbeing (expected welfare losses in percent of GDP) decreases rapidly with income per capita mostly due to better protection and lower asset vulnerability.



Map 1: Map of welfare risk in the countries included in the analysis

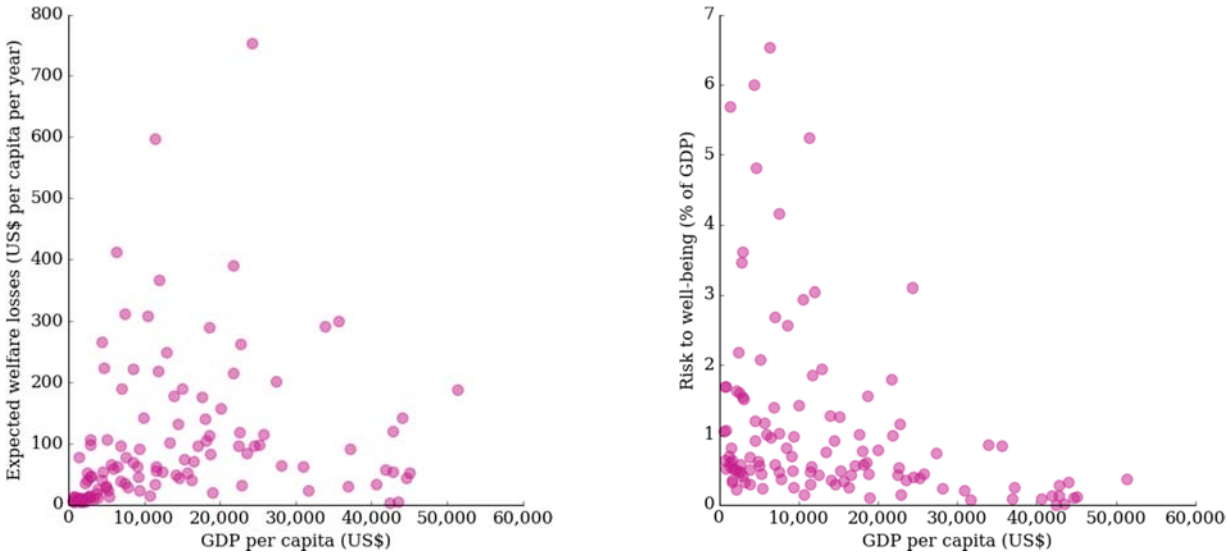
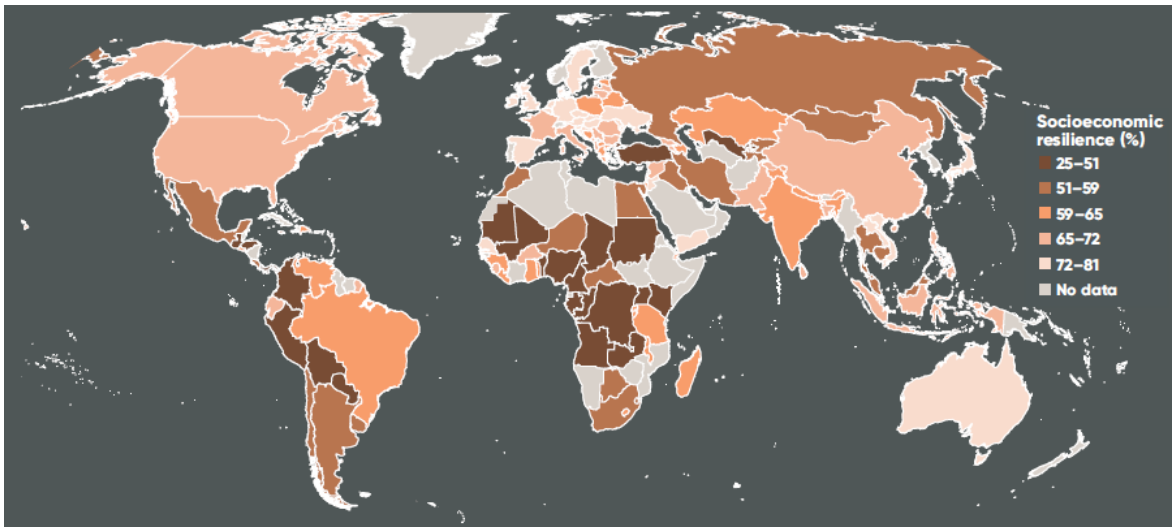


Figure 8: Welfare risk

Resilience averages 63% across our sample, ranging from 25% to 81%. Resilience in Malawi is 60%, which means that $1 of asset losses in Malawi has the same impact on welfare as a reduction of Malawi's national income by $1.7.[12] The resilience of all 117 countries is shown in Map 2.



Map 2: Socioeconomic resilience in 117 countries.

Resilience varies across countries of similar wealth **(Figure 9)** because welfare consequences depend on a multitude of factors, including preexisting inequality and safety nets to reduce the instantaneous

[12] Our measure of socioeconomic resilience does not include the fact that a reduction of national income by $1.7 has a larger impact in a low-income country than in a high-income country. While including this fact would be straightforward, it would imply to make inter-country welfare comparisons, which is not required in our analysis, and would lead average GDP per capital to dominate our estimates of resilience.

impacts of a disaster. This finding suggests that all countries – regardless of their geography or income level – can act to reduce risk by increasing resilience.

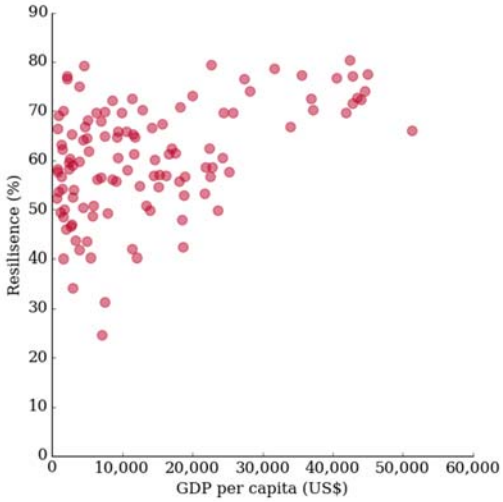


Figure 9 Socioeconomic resilience against GDP per capita

The lowest socioeconomic resilience in our sample is Guatemala, at 25% (i.e. $1 in natural disaster asset losses are equivalent to a $4 reduction in national income). This is due to the combination of high inequality (the bottom 20% receives only 3.8% of national income), a large vulnerability differential between the poor and the non-poor (poor people are almost six times more vulnerable than the rest of the population), and a relatively low level of social protection and access to finance, for the poor and non-poor.

The highest resilience is Denmark, at 81 percent (that is, well-being losses are only 25 percent larger than asset losses). This high resilience is mostly attributable to relatively low inequality (the income share of the bottom 20 percent is 9.1 percent) and large transfers from social protection, especially for the bottom 20 percent (poor people receive 68 percent of their income from transfers).

Interestingly, resilience is uncorrelated to the risk to assets, suggesting that countries did not build their socioeconomic resilience in response to asset risks. The reason is that many drivers of resilience are socioeconomic conditions that are outside the domain of traditional disaster risk management, which focuses on asset losses. No country has ever decided to reduce income inequality because of high exposure to natural hazards, even though inequality is a major driver of socioeconomic resilience.

Reducing poverty increases well-being, but because it increases wealth and the asset stock, it also increases asset losses from natural disasters. Many studies have looked at the effect of GDP growth on disaster losses, using regression or normalization techniques to separate the effect of growth from other drivers of disaster risk (Barredo 2009; Mendelsohn et al. 2012; Pielke et al. 2008; Simmons, Sutter, and Pielke 2012). They all conclude that losses increase with income, even though it is still debated whether disaster losses increase more slowly than income (and thus whether disaster losses decrease or increase over time when expressed in percentage of GDP). And while richer countries experience larger economic

losses, they suffer fewer casualties and fatalities than poorer countries (Guha-Sapir et al., 2013; Kahn, 2005).

Our analysis suggests that even if it increases asset losses, poverty reduction also increases global resilience such that well-being losses are virtually unchanged. Increasing the wealth of poor people by 10 percent in our model increases global asset losses by $3 billion per year (a 1 percent increase), but also increases resilience by 1 percent. The net effect is a decrease in well-being losses due to disasters, equivalent to a $500 million gain in consumption. Thus, poverty reduction not only increases average well-being, but also reduces the loss of well-being from natural disasters.

4.2. Policy options to reduce welfare losses from natural disasters

We now use the model to assess how much different policy actions can increase resilience and reduce welfare losses at the global level. We test 12 different policies.

To assess the potential benefits of better land-use plans or investments in infrastructure that protect the population against hazards such as drainage systems or dikes, we consider two policy experiments. In the first experiment, we reduce the fraction of the population exposed to natural hazards by 10 percent, targeting only poor people (among the bottom 20 percent in each country). If the entire world did so, asset losses would be reduced by about $14 billion a year, but the gain in well-being would be much larger, equivalent to an $82 billion increase in global income. In the second experiment, we still reduce the fraction of the population exposed to natural hazards by 10 percent, but this time targeting only nonpoor people (among the top 80 percent). In that case, avoided asset losses are much larger, $38 billion. But the well-being gains are smaller, equivalent to a $45 billion increase in global income.

To measure the benefits of constructing buildings that are more resistant to natural hazards, we explore the effect of reducing asset vulnerability. As for exposure, we look at two policies. In the first, we reduce by 30 percent the asset vulnerability of 10 percent of the population among the bottom 20 percent. In the second, we reduce by 30 percent the asset vulnerability of 10 percent of the population among the top 80 percent. Like exposure, focusing on poor people generates smaller benefits in terms of asset losses ($4.3 billion instead of $11 billion at the global level), but much larger benefits in terms of well-being ($28 billion instead of $13 billion).

We also evaluate the benefits of providing universal access to early warning systems globally, considering the impact on assets and disregarding the (large) benefits in terms of lives saved. Asset losses would be reduced by about $13 billion a year, and the well-being gain would be equivalent to an increase in income of $22 billion.

The seven other policies reduce welfare losses by increasing socioeconomic resilience, not by reducing asset losses. We test the impact of increasing income diversification through universal financial inclusion. It does not reduce the quantity or vulnerability of physical assets, but reduces the impact of a natural disaster on well-being, equivalent to an increase of $14 billion in consumption globally.

Financial inclusion—especially access to borrowing— and financial instruments—such as disaster funds—can also facilitate and accelerate reconstruction (de Janvry, del Valle, and Sadoulet 2016). We test this by reducing reconstruction duration by one-third. Globally, the loss of well-being from a disaster decreases, leading to a gain equivalent to $32 billion in consumption—that is, a 6 percent reduction in the global cost of disasters.

Stronger social protection is another way to increase income diversification. We tested an increase to at least 33 percent of share of the income from transfers for poor people, keeping their income unchanged (so we affect only the source of an unchanged income). Resilience would increase by 2.7 percentage points globally and global losses of well-being would fall by $17 billion a year (a 3.2 percent decrease).

Insurance products can provide protection at a lower cost and deliver large benefits through better risk diversification. However, providing everybody with access to market insurance is a long-term objective that faces multiple challenges, including weak institutional and legal capacity, and high transaction costs, especially for poor people. We tested premium-financed universal access for insurance to the nonpoor (the top 80 percent in each country) so that 25 percent of their losses is covered. That would increase resilience by 2.4 percentage points, to 63.4 percent, and would produce well-being gains worth $19 billion a year.

Finally, a growing body of evidence indicates that social insurance and social safety nets are efficient tools to support poor people affected by disasters, especially when these tools are designed to adjust and scale up quickly. To assess the potential benefits from generalizing such instruments, we tested a policy package that includes (1) financial instruments (reserve fund, contingent finance, risk-sharing instrument, or insurance product) so that the government has access to enough liquidity and resources for the post-disaster response; and (2) a preparation and contingency plan so that the budget can be reallocated to disaster victims in a timely fashion, with the objective of providing all victims with a uniform cash transfer that is calibrated to cover 80 percent of the losses suffered by the bottom 20 percent. Resilience increases 2 percentage points on average compared with the current situation. This would represent an additional gain in well-being of almost $13 billion. Our analysis also shows the complementarity between interventions that facilitate access to financial resources in the aftermath of disasters and interventions that improve preparedness (such as registries and automatic scaling-up mechanisms). Combined, these interventions produce much larger benefits than the sum of the two performed independently. The next section provides more insights on the economics of insurance products and adaptive social protection.

In addition to the global assessments presented previously, we tested these policies in each country, as shown in Figure 10 for Malawi and Figure 11 for Sweden (all 117 policy cards are available online). In both countries, the most efficient policy action to reduce welfare losses is to reduce exposure of poor people. But in Malawi, increasing social transfers for poor people to 33% comes second (while in Sweden, this share is already above 33%), followed by reducing asset vulnerability for poor people (it is already low in Sweden).

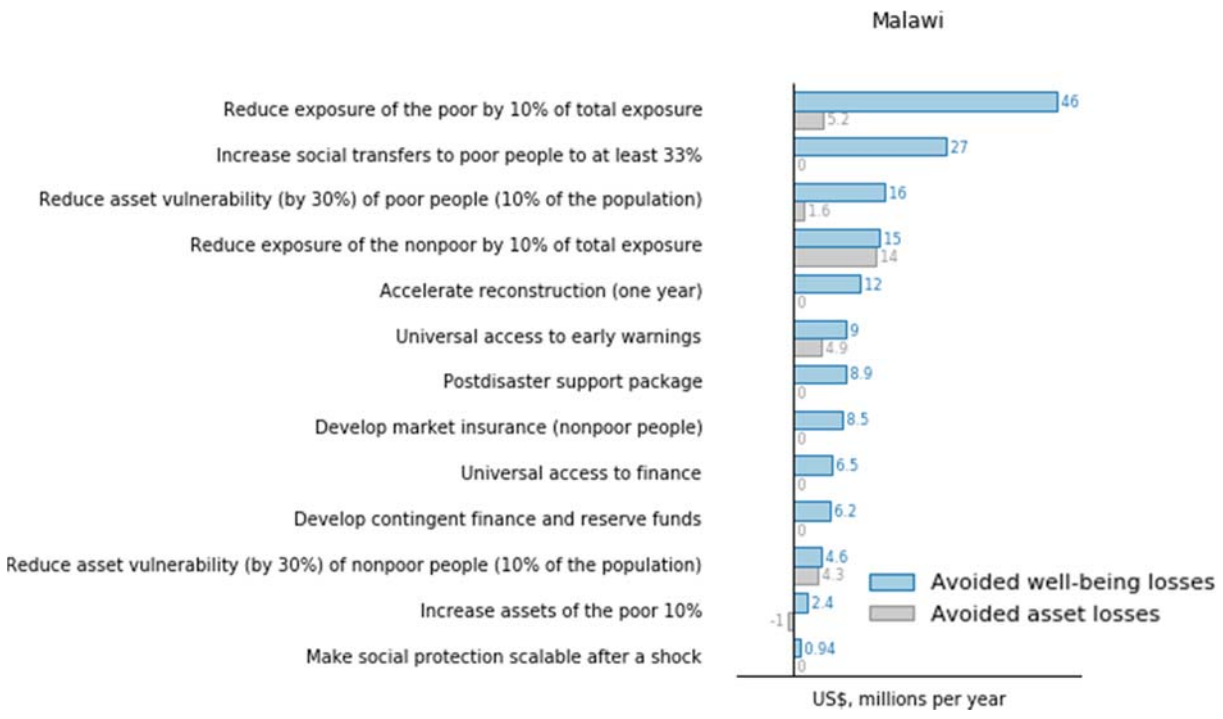


Figure 10 Policy card for Malawi.

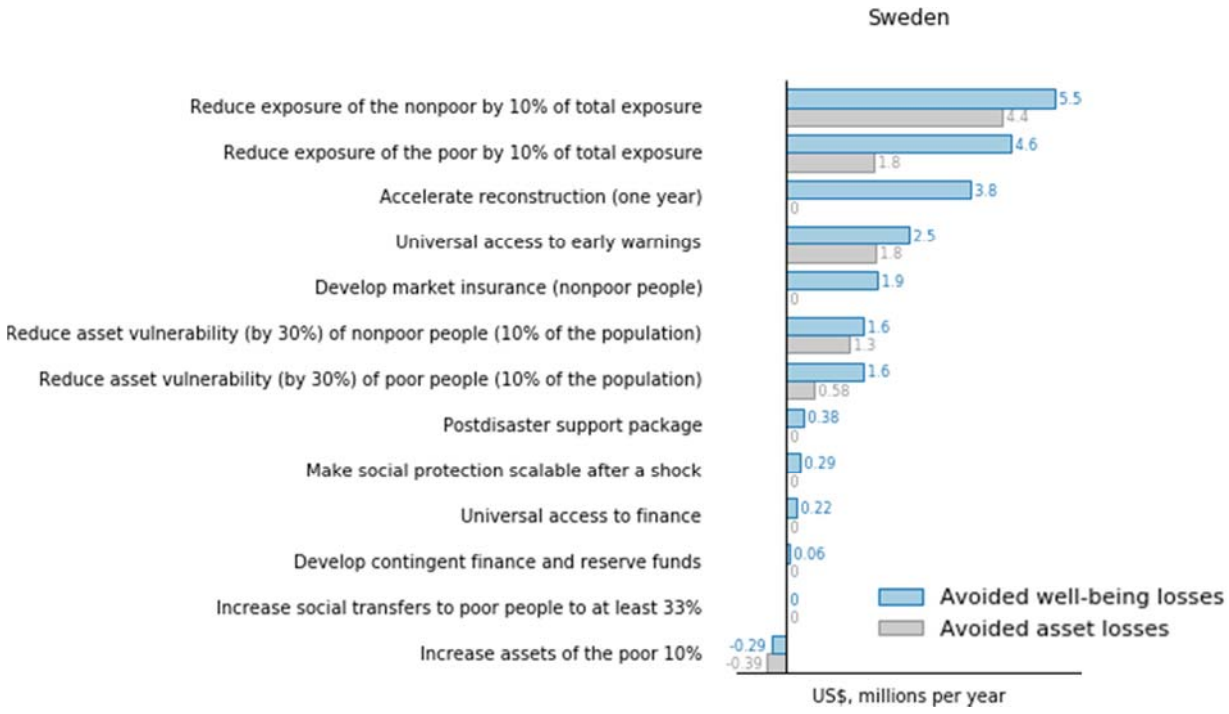


Figure 11: Policy card for Sweden.

These estimates can serve as an input to a cost-benefit analysis that would also need to account for the cost of these options and their benefits unrelated to resilience. For instance, developing social protection brings benefits that go beyond increased resilience and include economic benefits even in the absence of

shocks: an analysis of resilience cannot alone determine the desirability of such a policy. However, the policy cards can contribute to a discussion on a broad set of options to reduce natural risks and increase resilience, and ensure all options are discussed, from preventive actions like flood zoning to ex-post options like insurance, contingent finance and social protection. The scorecard provides an integrated framework to discuss and compare these options, and could even help break the silos in governments and local authorities, where ministries or departments in charge of social protection, building norms and urban planning may not work well together or not even consider flood risks in their decisions.

Our analysis of Malawi and Sweden – and the 115 other countries – is a first-round estimate using globally open data. It is a starting point for policy design and should be complemented by local studies (Aerts et al., 2014; Keating et al., 2014; Michel-Kerjan et al., 2013). At the local or national level, for instance, the flood risks from the global model can be replaced by results from local analyses at higher resolution, including flash floods and small basins. Local data on flood protection and better exposure data can often be mobilized (Aerts et al., 2014). And socioeconomic characteristics can be refined, accounting for instance for the institutional capacity to scale-up social protection beyond what a global database can reasonably aim at providing (Pelham et al., 2011). But in spite of all these limits, our global approach may contribute to the monitoring of country and global progress in terms of resilience, and our findings already provide insights into promising policy options, such as adaptive and well-targeted social protection, and show that "good development" increases resilience, especially if it reduces poverty and improves social safety nets.

The comparison between Sweden and Malawi illustrates that our results are country-specific: some factors are more important in some countries that in others. For instance, a low exposure is even more important in countries with a weak social protection system. Or a good post-disaster support delivery mechanism matters only where the government has resources to distribute after a shock. This variability supports the choice of using a model to assess resilience, instead of a weighted average of sub-indicators, such as most other indicators for vulnerability or resilience, in which the weights are global and cannot be adjusted to local circumstances.

4.3. Comparison with other indicators

Several other indicators measure resilience and risk at the country and sub-national level, work which our analysis has built on. Importantly, these indicators have different boundaries: some of them (e.g., InfoRM) include fragility and conflicts. Others – such as ND-GAIN – try to measure the ability to adapt to climate change, and thus include long-term trends that may not materialize through natural hazards and disasters (e.g., increasing water scarcity). As a result, these indicators cannot be directly compared among each other or with the indicator proposed in this paper. However, all these indicators tend to measure similar socioeconomic "capacities," namely the ability to avoid, resist and absorb shocks, and are thus closely related.

In this sub-section, we review existing indicators and compare our results on resilience and risk with three well-known country-level indicators, ND-GAIN, InfoRM, and WRI, for which data are available online.

4.3.1. Existing indicators

UNISDR – HFA2 Indicator System. The HFA2 indicator system, which was proposed for discussion in 2014, aims to revise the 22 existing HFA core indicators on disaster risk management and link input indicators to outputs and outcome. At the Third UN World Conference on Disaster Risk Reduction in Sendai in March 2015, seven global targets for disaster risk reduction were agreed upon to guide indicator development.[13]

EU-JRC – InfoRM. InfoRM, released in 2015, measures the risk of humanitarian crisis and disasters and how the conditions that lead to them affect sustainable development. It is global and open-source. Risk is calculated as the product of three, equally weighted components: (1) hazard and exposure, (2) vulnerability, and (3) lack of coping capacity. Hazard and exposure is sub-divided into natural and human sub-indicators. Vulnerability is sub-divided into socioeconomic vulnerability and vulnerable groups, and lack of coping capacity is sub-divided into institutional and infrastructure. Results are available online.[14]

ND-GAIN – Index. A country's ND-GAIN score is the readiness score minus the vulnerability score for each country. Vulnerability measures a country's exposure, sensitivity, and capacity to adapt to the negative effects of climate change looking at six sectors: food, water, health, ecosystem services, human habitat, and infrastructure. Each of the six sectors provides a measure, and the vulnerability score takes the simple mean of these six scores. Readiness measures a country's ability to leverage investments and convert them into adaptation actions, looking at three components: economic readiness, governance readiness, and social readiness. For the calculation, each sub-indicator of vulnerability and resilience is scaled to give a score between 0 and 1, with all components weighted equally. Results from ND-GAIN can be viewed online.[15]

OECD – Guidelines for Resilience Systems Analysis. The OECD has completed a "how-to-guide" for a Resilience Analysis Tool, which has been piloted in 3 countries, and allows users to design roadmaps for boosting resilience in a system, community or state. Indicators are based on the status of assets identified for resilience, with type/status of assets context-specific (OECD 2014). The relevant indicators depend on the resilience strategy followed in a given country. The process is based on a consultation process in the country (initial pilot took 5 weeks – 2 weeks preparation and 3 weeks in-country; consultations to follow will likely take less time). The methodology was first developed through a pilot in the Democratic Republic of Congo, and has since also been piloted in Lebanon and Somalia. The results from the three pilot countries can be viewed online.[16]

GIZ – Two indicator-based approaches. Germany's Development Agency, the GIZ, has developed a Vulnerability Assessment Sourcebook, which provides guidelines for developing vulnerability indexes and for using this index to measure changes over time (GIZ 2014). The GIZ is also currently developing a methodology on Climate Resilience Indicators, which aims to assess resilience at country-level based on globally available data complemented by country-specific data. An example of a Climate Resilience

[13] http://www.wcdrr.org/uploads/Sendai_Framework_for_Disaster_Risk_Reduction_2015-2030.pdf
[14] http://inform.jrc.ec.europa.eu/Results/Global
[15] http://index.gain.org/
[16] http://www.oecd.org/dac/risk-resilience.htm

Indicator for Mexico is calculated as the sum of three, equally weighted components: (1) absorptive capacity, (2) adaptive capacity, and (3) transformative capacity. Absorptive capacity measures the ability to prepare for, mitigate or recover from the impacts of negative events using predetermined coping responses (e.g. early warning systems). Adaptive capacity measures the ability to adjust to better respond to future shocks (e.g. adjusted planting behavior). Transformative capacity measures the ability to fundamentally change when existing conditions become untenable (e.g. livelihood transformation). The report on climate resilience indicators can be viewed online.[17]

IDB – Disaster Indicators. The Inter-American Development Bank has developed several indicators, including the (1) Disaster Deficit Index (DDI), (2) Local Disaster Index (LDI), (3) Prevalent Vulnerability Index (PVI), (4) Risk Management Index (RMI), and the (5) Index of Governance and Public Policy for DRM (iGOPP). The (1) DDI measures the economic loss a country could suffer when a catastrophic event takes place, and implications in terms of resources needed to address the situation. It is calculated by dividing the losses from a *maximum considered event* by the *economic resilience* of a government (that is, the availability of internal and external funds). The (2) LDI measures the propensity of a country to experience small-scale disasters and their cumulative impact on local development. It is calculated as the sum of three local sub indicators on the number of deaths, people affected, and economic losses, with associated weights. The (3) PVI measures vulnerability conditions by measuring exposure in prone areas, socioeconomic fragility and lack of social resilience. It is calculated as the average of three types of composite indicators – on exposure, fragility, and resilience, with associated weights. The (4) RMI measures risk management performance. It is calculated as the average of four composite indicators – risk identification, risk reduction, response and recovery, and governance and financial protection, with associated weights. The new indicator, iGOPP, which is a combination of 246 binary indicators, is used principally for verifying the status of public policy. Application of RMI, DDI, LDI, PVI to countries in Latin America and the Caribbean can be viewed HERE.[18] Application of IGOPP to six countries can be found HERE.[19]

Zurich Flood Resilience Alliance – Measuring community resilience. Zurich Bank, along with the International Institute for Applied Systems Analysis (IIASA), the University of Pennsylvania – Wharton, INGO, and the Red Cross, have joined a project to estimate the resilience of communities in Nepal, Bangladesh, and Peru. The research program, which has only just started, will develop a methodological framework based on systems analysis to measure community resilience and address the behavioral, economic and policy obstacles to effective community flood resilience. The approach will be piloted in many developing countries, for example in Bangladesh (see more HERE). More information on the Flood Resilience Alliance can be viewed HERE and HERE.

World Development Report 2014 – Indicator of Risk Preparedness. As part of the World Bank's World Development Report 2014, an indicator of risk preparedness was developed, which comprises measures

[17] https://gc21.giz.de/ibt/var/app/wp342deP/1443/wp-content/uploads/filebase/me/national-level-me(2)/giz2014-en-assessing-resilience-discussion-paper.pdf
[18] http://www.iadb.org/en/topics/natural-disasters/disaster-risk-indicators/disaster-risk-indicators,1456.html
[19] http://publications.iadb.org/handle/11319/6738?locale-attribute=es

of assets and services across four categories – human capital, physical and financial assets, social support, and state support (Foa 2013; World Bank 2013).

The Center for Global Development's Vulnerability to Climate Change Index. This index provides an accounting of climate change vulnerability, by developing a Climate Drivers Index for 233 states, and quantifies vulnerability to climate change as a result of (1) weather-related disasters, (2) sea-level rise, and (3) reduced agricultural productivity. This Climate Drivers Index is also combined with data on governance and per capita income to incorporate measures of resilience, and with data on project effectiveness within countries. The full paper outlining the methodology by Wheeler (2011) can be found HERE.

Barr et al (2010) – Climate Change Impact Rankings. This paper provides an indicator of climate change impact in 131 countries and discusses how adaptation funding might be allocated based on this measure. The indicator includes dimensions of physical impact, adaptive capacity, and implementation capacity. On physical impact, four sub-indicators are included, on agriculture, disasters, health, and coastal zones. On adaptive capacity, separate scores are developed which incorporate sub-indicators such as the age dependency ratio and the Gini coefficient. For implementation capacity, data from the World Bank's Country Policy and Institutional Assessment and Annual Review of Portfolio Performance are used. An overall vulnerability score is derived by subtracting the score for adaptive capacity from the score for impact. The full paper can be found HERE.

DARA's Climate Vulnerability Monitor. The Climate Vulnerability Monitor provides an assessment of climate change impact in 184 countries. The Monitor provides an assessment of socioeconomic vulnerability, covering four impact areas, including (1) habitat change, (2) health impact, (3) industry stress, and (4) environmental disasters. Each of the four impact areas is composed of several sub-indicators. The Monitor assesses vulnerability in terms of the impact of climate change on each of these sub-indicators, with the impact expressed as higher mortality (health), costs relative to GDP (for habitat change and industry stress), or both (for environmental disasters), in 2010 and 2030. More information can be found HERE.

UN University and University of Bonn's World Risk Index. The World Risk Index is a tool used to assess the disaster risk of a country. The objective of this index is to measure the vulnerability to natural disasters in 171 countries, and is composed of four main indicators: (1) exposure to natural hazards; (2) susceptibility which depends on socioeconomic conditions, (3) coping capacity which is dependent upon preparedness, governance, and security, and (4) adaptive capacity relating to future natural events. The Index is calculated from 28 sub-indicators from openly available data. More information can be found HERE.

GermanWatch's Global Climate Risk Index. The Global Climate Risk Index, published annually, analyzes to what extent countries have been affected by the impacts of weather-related loss events, including storms, floods, and heatwaves. The Index is populated using data from Munich Re's NatCatSErVICE and the International Monetary Fund, among other sources. The following indicators were used in the Global Climate Risk Index: number of deaths, number of deaths (population-adjusted), the sum of losses, and

losses per unit of GDP. Each country's index score is derived from the country's ranking in each category, based on weighting. More information on the methodology can be found HERE.

4.3.2. Comparison of our results with ND-GAIN, InfoRM, and the World Risk Index

The figure below provides a series of scatter-plots, comparing our indicators of resilience and risk to ND-GAIN, World Risk Index and InfoRM's indicators. We also plot against GDP per capita for reference.

These scatterplots provide two notable observations. First, our resilience indicator is broadly consistent with existing indicators. This is interesting considering the different boundaries and time horizons of these three indicators. This correlation suggests that our resilience is linked to basic economic characteristics that are also considered important by other groups for the vulnerability to climate change (ND-GAIN) or humanitarian crises (InfoRM).

The second observation is that while ND-GAIN, InfoRM and WRI include hazard and exposure in their modules, they are not well correlated with our risk measure – in fact they appear better correlated with our resilience measure. This is of course a product of how risk is measured in each initiative. But it may also imply that ND-GAIN, WRI, and InfoRM may better capture the socioeconomic dimensions related to "resilience" (e.g. adaptive capacity, readiness), rather than the overall risk (and in particular the fact that exposure and hazard vary by orders of magnitude across countries, which our risk measure is the only to capture). An important implication is that these indicators are likely to underestimate the difference in risk levels across countries.

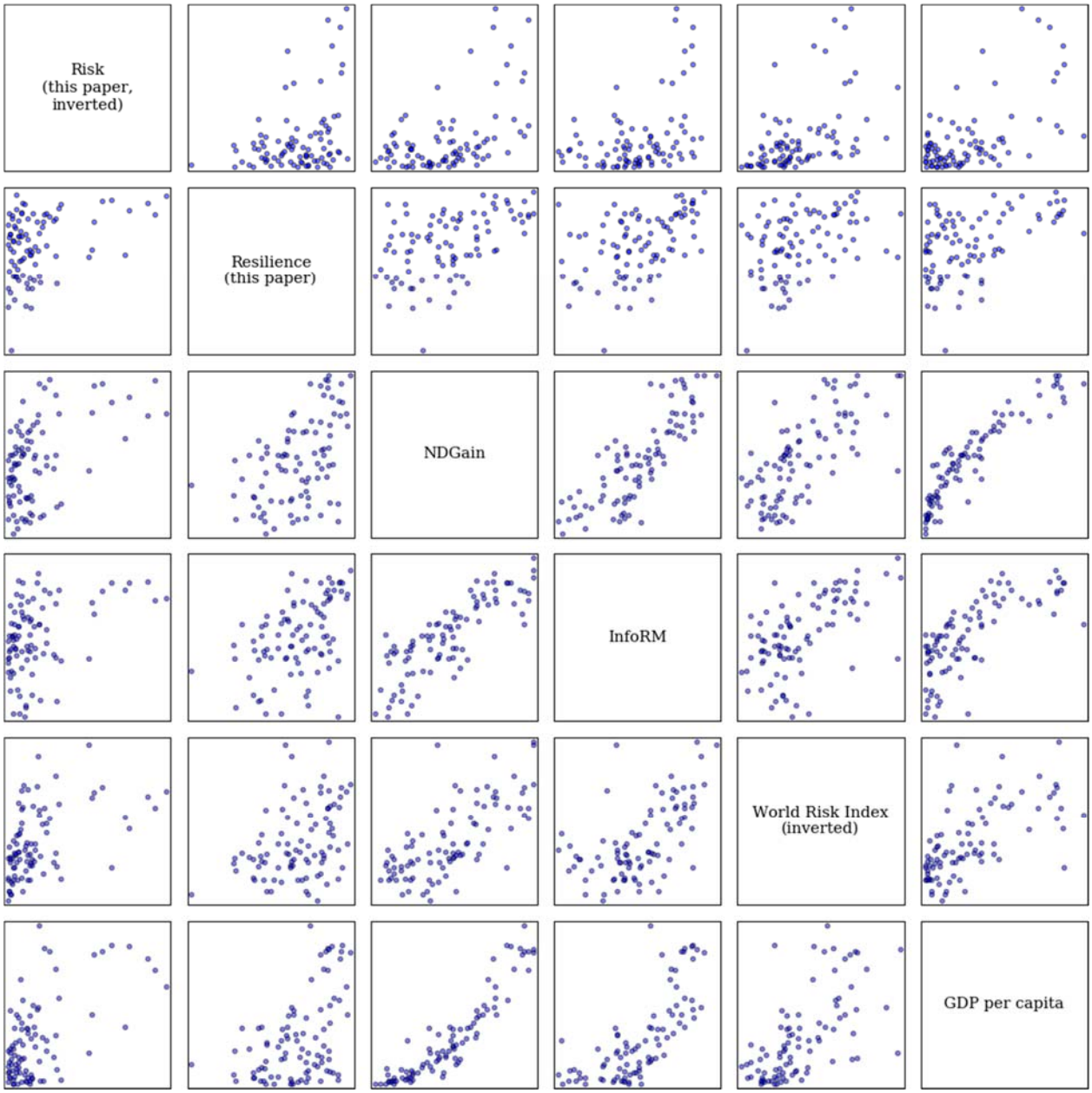


Figure 12: Comparison our measures of risk and resilience to InfoRM and ND-GAIN

5. The role of adaptive social protection in reducing welfare losses due to natural disasters

This section takes a closer look at the benefits from post-disaster government transfers and adaptive social protection in terms of resilience and well-being. We look at adaptive schemes (like in Ethiopia during the 2015 drought) and at ad hoc government or international transfers (like in Pakistan after the 2010 floods), and how they can affect our estimate of resilience.

5.1 Post-disaster transfers are good economics

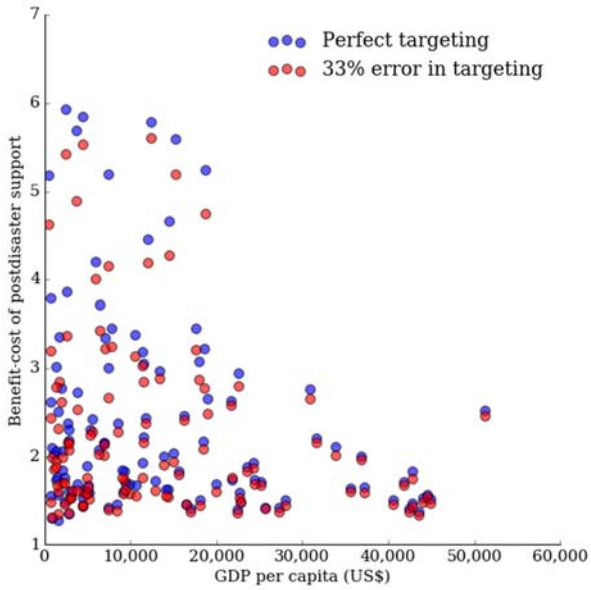
We first calculate the benefits of post-disaster support (including the supplementary amounts transferred as part of an adaptation social protection system). To do that, we look at the benefit of transferring $1 to each affected individual. In this simulation, we include targeting errors, assuming that 33% of the affected individuals are "missed" by the support; and that the same number of people are wrongly compensated. (This is close to the performance of the phase II of the Pakistan's Citizen's Damage Compensation Program, which had a 30-32% exclusion error.) The benefit-cost ratio represents the average benefit in welfare that is generated by $1 used for the program. If the ratio is higher than one, it means that the benefit is larger than an equivalent increase in GDP in the country.

The analysis suggests that these transfers are a good economic choice, even with targeting errors: the benefit-cost ratio is higher than 1.3 in all countries and its average value across countries is 2.2 (weighting countries by their population, see Figure 13). And in 11 countries—Angola, Bolivia, Botswana, Brazil, Central African Republic, Colombia, Honduras, Lesotho, Panama, South Africa, and Zambia—every $1 spent on post-disaster transfers yields well-being benefits of more than $4 (Table 4).

Post-disaster support makes sense in poor and rich countries, but countries with the highest benefit-cost ratios have an income per capita below $25,000 per year (in PPP USD). In general, post-disaster transfers are most desirable where the exposed population is the poorest, and where poor people have a high vulnerability (for instance because of building quality or low income diversification); this is for instance the case in South Africa or Honduras. In some countries, the benefit-cost ratio is relatively low – such as in Slovak Republic – because the better-off people are more exposed; in that case, post-disaster transfers are going toward the better-off whose income after the shock is still larger than the income of unaffected poor people. Overall, targeting errors have only a limited impact on the benefit-cost ratio. This question is explored in more detail below.

Figure 13: Post-disaster transfers are good economics – the benefit-cost ratio is often much larger than one.

(Benefit-cost ratio of post-disaster support, assuming that transfers are proportional to losses, and under two assumptions regarding targeting.)



If raising these resources has a cost – for instance if the collection and distribution of $1 leads to 25 cents in losses or because raising more taxes creates a cost for the economy – then the benefit-cost ratio is reduced by the same amount. These losses are different from poor targeting: instead of being received by the wrong person, these 25 cents are wasted, for instance through administrative costs or because higher tax collection reduces economic activity. Here for instance, if the cost of $1 of public resource is more than $1.30, then the benefit-cost of post-disaster transfers in Niger becomes lower than one. Estimates for the cost of public resources vary widely (Table 5), and estimates are made difficult by multiple conceptual and practical issues (Massiani and Picco 2013; Browning 1976; Dahlby 2008). But in countries where raising taxes is particularly costly – because of administrative cost or because of the impact of labor supply or investment – the benefit-cost ratio of post-disaster support is reduced accordingly. (In this model, we assume proportional taxation, which is not optimal with our assumption regarding the decreasing return of consumption.)

Table 4 – Top 20 countries where the benefit-cost ratio of post-disaster transfers are the highest and the lowest (assuming 33% targeting error).

Countries with highest benefit		**Countries with lowest benefit**	
Country	**Benefit-cost ratio**	**Country**	**Benefit-cost ratio**
South Africa	5.6	Niger	1.3
Honduras	5.5	Sweden	1.3
Lesotho	5.4	Mali	1.3
Botswana	5.2	Cambodia	1.3
Zambia	4.9	Kazakhstan	1.4
Panama	4.7	Slovenia	1.4
Central African Republic	4.6	Denmark	1.4
Brazil	4.3	Belarus	1.4

Colombia	4.2	Ukraine	1.4
Angola	4.2	Armenia	1.4
Bolivia	4.0	Slovak Republic	1.4
Swaziland	3.4	Moldova	1.4
Kenya	3.4	Germany	1.4
Paraguay	3.2	Czech Republic	1.4
Guatemala	3.2	Pakistan	1.4
Venezuela, RB	3.2	Romania	1.4
Congo, Dem. Rep.	3.2	Azerbaijan	1.4
Ecuador	3.1	Tajikistan	1.5
Peru	3.0	Belgium	1.5
Costa Rica	2.9	Netherlands	1.5

Table 5– Estimates of the opportunity cost of public funds differ widely

(Estimates of the opportunity cost of public fund in difference countries, from (Massiani and Picco 2013).

Estimates of the Opportunity Costs of Public Funds

Country	Estimation	Source
Australia	1.25	
Canada	1.2–1.3	Ruggeri (1999)
Philippines	2.48	Jones, Tandon, Vogelsang (1990)
France	1.3 and 1.5	Commissariat Général du Plan (1973 and 1985)
	1.1–1.4	Applying Snow and Warren's formula (1996)
	1.2–1.3	Bernard (1976)
	1.12	Bernard and Vieille (2003)
	1.13–1.3	Lebègue et al. (2005)
	1.05–1.2	Quinet (2006) quoting literature
	1.3	Auriol and Blanc (2007)
		applying Snow and Warren's formula (1996)
Japan	1.03	Bernard and Vieille (2003)
Malaysia	1.20	Jones, Tandon, Vogelsang (1990)
Western countries	1–1.5	Browning (1987)
	1.3–1.5	Laffont (1999)
United Kingdom	1.3	Florio (2002)
	1.3	
Russia	1.23	Bernard and Vieille (2003)
Thailand	1.19–1.54	Jones, Tandon, Vogelsang (1990)
USA	1.17–1.56	Ballard (1990)
	1.02	Bernard and Vieille (2003)

5.2 Uniform transfers are often more cost-effective than proportional transfers

There are different ways of allocating post-disaster support. Some countries allocate support proportionally to the losses, with a budget constraint. In Vietnam, for instance, the post-disaster support system is based on an estimate of damages per household. The Emergency Assistance Program is the main social assistance response to disaster. Introduced in 2007, the program provides cash and rice to disaster-

affected households, as a function of their losses. Compensation for destruction or serious damage to housing or relocation following landslides or floods is VND 5 million per household (USD 235). Similarly, agricultural losses are compensated in a proportional manner (see Box 1). Richer households who lose more in absolute terms are therefore likely to receive a larger compensation.

Such a distribution rule mimics insurance. Because rich people usually lose more in absolute terms, such a scheme tends to transfer more resources to rich than to poor people. And because the resources available for post-disaster support are usually small compared to the total losses, a proportional scheme leads to a situation where compensation represents a very small share of individual losses, reducing the usefulness of the compensation.

Box 1: MARD Disaster Benefits

Support for Crops (30% or more)

- Plain rice cultivation area damaged more than 70%,1 million VND/ha (about USD 48); damage from 30-70%, 500,000 Dong/ha (USD 24);
- Hybrid rice acreage damaged more than 70%, 1.5 million/ha (USD 70); damage from 30-70%, 750,000/ha (USD 35)
- Corn/vegetable acreage damaged more than 70%, 1 million VND/ha (USD 48); damage from 30-70%, 500,000 Dong/ha (USD 24)
- Industrial crops/fruit trees, perennial damage more than 70%, 2 million/ha (USD 94); damage from 30-70%, 1 million VND/ha (USD 48)

Support for Lost Livestock:

- Bird, from 7,000-15,000 Dong/animal (USD 0.3 to USD 0.7)
- Pig, 500,000 Dong/hatchling (USD 24)
- Bovine, equine, 2 million VND/animal breeds (USD 94)
- Deer, sheep, goats, 1 million VND/hatchling (USD 48)

Support for Aquaculture, Seafood Losses (30% or More)

- Area suffered more than 70%, 3 million - 5 million/ha; damage from 30 -70%, 1 million-3 million/ha (USD 48 to USD to USD 144)
- Cages suffer damage more than 70%, from 3 million - 5 million VND/100 m^3 cages (USD 144 to USD 240); damage from 30-70%, 1 million -3 million Dong/100 m^3 cages (USD 48 to USD 144)

Source: Decision No.: 187/2010/TT-BTC (2009) Circular Provisions on the Mechanism, Policy Support Plant Breeding, Livestock, Aquatic Production to Recover the Losses Due to Natural Disasters, Disease

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Another option to distribute post-disaster support is to provide a uniform amount to all people being affected. Considering how difficult and costly it is to measure individual losses after a disaster, a uniform transfer to those affected represents a welcome simplification of the targeting mechanism. In India, post-disaster support often takes the form of an ad hoc financial transfer, such as the 5,000 rupees provided to victims of the 2005 floods in Mumbai. In Pakistan after the 2010 floods, eligible households also received uniform amounts from the federal government's Citizen's Damage Compensation Program (CDCP), a rapid response cash grant program. In phase one, eligible households were given a one-off cash grant in the amount of PRK 20,000 (about US$213), based on funds available to cope with the urgent needs of a very large flood-affected target population. In phase two, the size of the grant to eligible

households was doubled to PRK 40,000 (around US$ 426), a more suitable amount to support recovery, provided in two installments of PRK 20,000 each.

The amount provided is often very small – maybe significant for poor people, but negligible for the richer part of the population. In Mumbai after the 2005 floods, average losses were around 50,000 rupees, and the post-disaster transfer was only 5,000 rupees. In Bangladesh following the 1998 Great Flood, for instance, post-flood transfer amounts were too small to make a difference: they represented only 4 percent of total household monthly expenditure for poor households, and 2 percent for all households. Household borrowing highlights this limit: poor households affected by the flood borrowed about six to eight times more compared to the level of government transfers. It means that post-disaster does not replace insurance, and do not cover the loss of the middle-class (see also below).

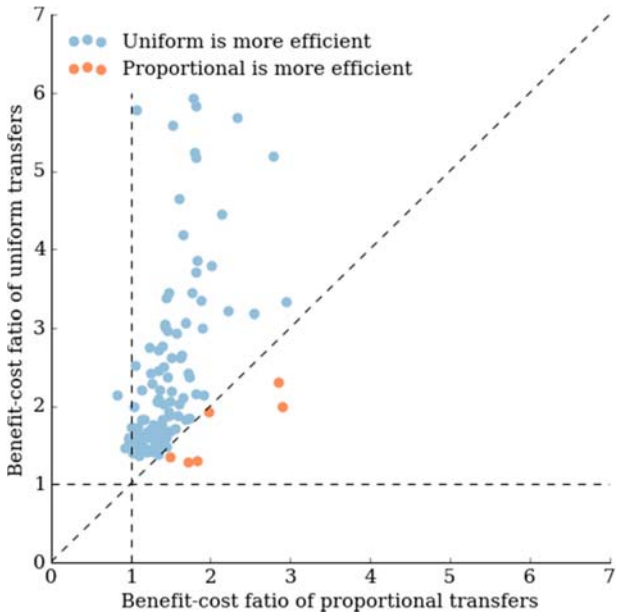
If we assume that the same budget - $1 per affected individual – is used for post-disaster support, we can compare the benefit-cost ratio with the two approaches. The results are presented in Figure 14. In most countries, the welfare benefit from $1 per affected individual in post-disaster support is higher if the support is distributed uniformly to the population. On average, the benefit-cost ratio is higher by 0.9 if support is distributed equally. The six exceptions (Cambodia, Greece, Mali, Mauritania, Niger, Thailand) are countries where poor people lose more than non-poor people *even in absolute terms*. This is the case where poor people are much more vulnerable than the rest of the population, and/or where inequality is low (so that the difference in vulnerability dominates the difference in pre-disaster wealth).

Even though benefit-cost ratios are lower if support is proportional to losses, only four countries have a benefit-cost ratio lower than one in that case (Azerbaijan, Georgia, Hungary, Ireland), and only Georgia has a ratio below 0.9. These countries are countries where poor people have a highly diversified income – especially due to social protection transfers – that makes them less vulnerable.

The ten countries where the difference between uniform and proportional transfers is the largest – in favor of uniform transfers – are South Africa, Lesotho, Botswana, Honduras, Panama, Central African Republic, Zambia, Brazil, Bolivia, and Angola. They are countries with large inequality (in terms of pre-disaster income and in terms of vulnerability), where post-disaster support would go disproportionally toward the better-off with a proportional scheme.

Figure 14: Uniform post-disaster transfers often have higher benefit-cost ratios than transfers that are proportional to losses, because the later lead to higher transfers for the better-off.

(Benefit-cost ratio of post-disaster support when transfers are uniform, compared with then transfers are proportional to losses)



These results however make the important simplification that the amount of losses is mostly driven by vulnerability and wealth – and thus by the income level of the affected household. It disregards the variance in hazard and assumes that all individuals of the same income class that are affected are losing the same fraction of their income. In the presence of a large variability of losses – e.g., after a windstorm, some houses are completely destroyed while others have minor damages to roof and windows –the value of post-disaster transfers that are proportional to losses would increase.

5.3 Post-disaster transfers and adaptive social protection do not replace insurance

This analysis starts from the assumption that post-disaster government transfers are designed to support the most in need. Under this assumption, it is preferable to support a non-affected person than an affected person, if the non-affected person is poorer than the affected one after the shock. This is a fundamental difference with insurance, which is designed to compensate for a fraction of the losses, irrespective of the income level or the level of need. This difference is justified by (1) who pays for the protection (the taxpayer for government transfers vs. the protected individual in case of insurance); (2) how the price is calculated (taxes are usually determined by income and consumption levels, while insurance premium depends on the average losses).

But governments in post-disaster situations cannot only support the poorest, especially if even the better-off have no access to risk management instruments such as borrowing and insurance.

There is an economic rationale to help the population – even the relatively wealthy – to repair and rebuild: their position in the economic system makes it important that they get back to work and restore their productivity as soon as possible. Evidence from the floods in Thailand in 2011 shows that people with no direct damages from the flood saw a reduction in income similar to the reduction of income for directly-affected people, due to spill-overs in the economic system (Noy and Patel 2014). These spill-overs – at least those through reduced demand – are likely to be mostly dependent on the impact on the better-off, since they represent a large fraction of overall demand.

There is also a political economy rationale: governments cannot stay idle as some people struggle to cope with and repair damages, even if these people are not the worst-off in the country. There is usually a strong demand for support after disasters, and the better-off have often more political influence and voice to lobby for support.

These two reasons explain why post-disaster transfers or adaptive social protection are not substitutes for market insurance. If social protection is designed to help the poorest and most vulnerable, it cannot provide an insurance service to the middle-class and the better-off, unless the government is ready to spend extremely large resources. In practice, governments face the double objective of helping the poorest and most vulnerable and compensating the affected population, and scarce resources makes it difficult or impossible to meet these two goals.

The classical indemnity insurance products are commonplace in high-income countries and are based on the observation of losses, with insurance payments triggered once losses occur. Since premiums are paid by the beneficiaries, they create much less fairness and distributional issues (even though premiums are often subsidized in practice). Classical indemnity insurance requires that robust data be available for the insurer to assess risks ex-ante – something that is often lacking in developing countries (Rogers and Tsirkunov 2013). And loss assessment may be costly if it requires that an expert visits every victim.

High penetration of market insurance removes the trade-off for the government between compensating the victims and supporting the poorest, especially with scarce resources. So policies to increase market insurance penetration are also important for the poor, even if they do not benefit directly from insurance. They benefit indirectly if the government – who do not need to compensate the middle-class anymore – can concentrate resources on them after a disaster.

Making market insurance available is often not enough; even in developed countries, penetration of indemnity insurance against natural hazards remains low in the absence of additional policies and actions. Countries with high insurance penetration are countries (i) where insurance is subsidized, as with floods in the US with the National Flood Insurance Program; (ii) where insurance is mandatory and backed by the government – such as the Turkish insurance against earthquakes and fires, which is an excellent example of how insurance access can be increased in middle-income countries; or (iii) where insurance is mandatory, cross-subsidized and backed by the government, the case of France's Cat-Nat flood and drought insurance (Paudel 2012).

5.4 Post-disaster transfers increase resilience – even if they are imperfect

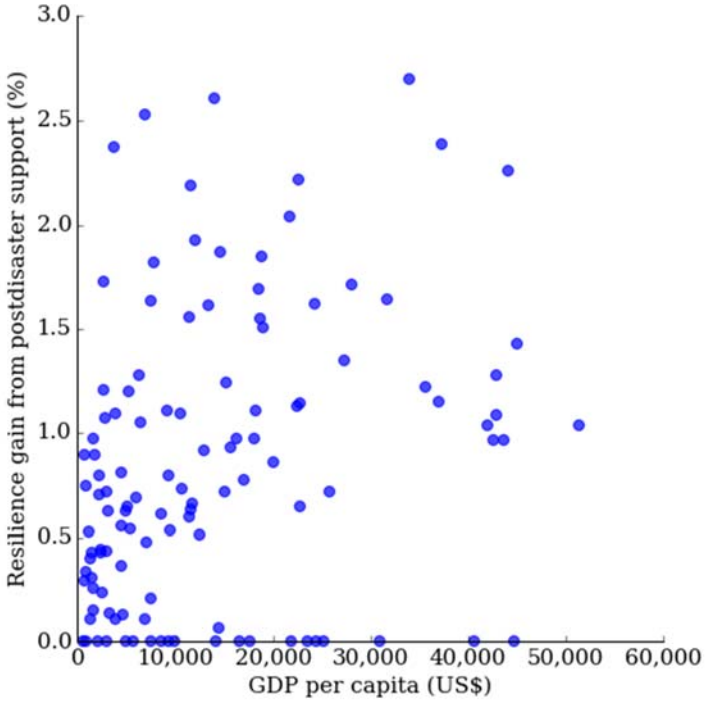
Figure 15 shows the resilience gain thanks to post-disaster transfers modeled in resilience estimation: a uniform transfer calibrated on the losses of the poor people, taking into account the limits in borrowing and ability to reallocate resources that countries face.

On average, resilience increases by 1.4 percentage points thanks to such post-disaster support. At the global level, on the 117 countries covered by our analysis, it is a gain of $11.8 billion per year, in terms of welfare. These gains in welfare are achieved by transferring – though post-disaster support and special taxes – $11 billion per year.

Resilience gains are growing with the GDP level, because richer countries tend to have higher capacity to fund and deliver post disaster transfers. But there are countries at all GDP levels without the capacity to mobilize resources after disasters (either because they lack access to liquidity or because they are unable to reallocate resources toward emergency support). All countries where resilience is not increased by post-disaster transfers are countries where (1) the government cannot access or reallocate the financing (i.e. low credit rating and no contingent finance arrangement in place); and/or (2) the government does not have any plan for post-disaster support. These include countries which have not reported anything under the Hyogo Framework for Action, and which might actually have better capacity than what we modeled.

Figure 15: Current capacities to provide post-disaster support to the population already increase countries' resilience.

(Resilience gains with estimates of the current ability of countries to distribute post-disaster support, compared with a situation with no post-disaster support, assuming that transfers are proportional to losses)



6. Discussion

Our socioeconomic resilience remains an imperfect metric, in the sense that it does not include all the dimensions discussed in the resilience field (Barrett and Constas, 2014; Engle et al., 2013; Keating et al., 2014). Our framework looks at the socioeconomic resilience, but disregards direct human and welfare effects (death, injuries, psychological impacts, etc.), cultural and heritage losses (e.g., the destruction of historical assets), social and political destabilization, and environmental degradation (for instance when

disasters affect industrial facilities and create local pollution). The framework proposed here is for socioeconomic resilience, not for a broader concept of resilience.

Issues related to conflicts and government stability are not explicitly recognized, even though they indirectly influence our results since fragile governments usually provide little social protection and have limited ability to respond to shocks. We also do not account for the possibility that a disaster (or the response to it) magnifies pre-existing conflicts.

Average losses for poor and non-poor people may not capture the full impact of the disaster: in each category, losses are heterogeneous and some households may lose everything, and experience long-term effects or fall into *poverty traps*. During the July 2005 floods in Mumbai, India, household surveys show that the median asset and income loss per capita was approximately Rs. 9,300, while the average loss was substantially higher at around Rs. 13,700 (Patankar and Patwardhan 2016). Losses across the population follow a lognormal distribution with a long tail: median losses are moderate, but some households lost almost all their income. For the people experiencing large losses, the welfare impact of the shock is not only related to the net present value of the flow of consumption losses, but also to possible long-term effects, such as reduction in food intake, health effects and disability, and exclusion from job markets, which can lead households to fall into poverty traps (Barnett et al., 2008; Carter et al., 2007; Kraay and McKenzie, 2014; Maccini and Yang, 2009). The risk of poverty traps is particularly acute for children, as severe health impacts or interruptions in education can have lifelong impacts on earnings. We disregard this risk as it is difficult to monetize. (Barrett and Constas, 2014) propose a definition of *development resilience* that focuses on the capacity of people to avoid such poverty traps.

Also, the ability of individual firms to cope with the shock and continue to produce in the disaster aftermath – the *static resilience* of (Rose, 2009) – depends on many factors that would need to be included in the analysis. Various methodologies have been proposed to assess these parameters, using input-output or general equilibrium models (Santos and Haimes, 2004; Rose and Wei, 2013; Hallegatte, 2014b) or explicit modeling of supply-chains (Battiston et al., 2007; Henriet et al., 2012). But more work is needed to assess this resilience based on the data and indicators that are available in all countries.

We have disregarded the impact on natural capital, in spite of its importance for the income of poor people across the world (Angelsen et al., 2014) and the impact of natural disasters on soils (through salinization or erosion), fish stocks, or trees. Including natural capital in the assessment would meet many data related issues, on the local importance of natural capital in income and on the vulnerability of natural capital to disasters.

Further, our framework does not address the ability to "build back better" after a disaster and the possibility for reconstruction to lead to an improved situation. It also takes the current exposure and vulnerability as a given, and investigates policy options without accounting for feedback in terms of risk-taking decisions. Better ability to manage risks – e.g., through access to insurance and social protection – could indeed have further positive economic impacts through more risk-taking, innovation, and specialization (Elbers et al., 2007; World Bank, 2013). It can also have negative impacts through moral hazard and excessive risk-taking (Michel-Kerjan, 2010). These feedbacks and relationships have to be

explored before any risk management policy is implemented, but they often depend on implementation details and cannot be assessed through a global analysis.

The response to a shock is not fully native to a country, but is also driven by foreign development assistance (Hochrainer, 2009), which is not explicitly taken into account in the indicator. We do capture some aspects of development assistance. For instance, countries may be able to provide social protection thanks to budget support from abroad (for instance, Ethiopia receives significant support for its Productive Safety Nets Program). Also, the ability to scale up support after disasters as included in the HFA reporting – depends on concessional resources and international support (e.g., through CAT-DDOs). Humanitarian and emergency response is not included in our analysis, however. This may create a "resilience bias" towards middle-income countries that need less to rely on overseas assistance. However, one positive aspect of not including humanitarian assistance is that countries with low resilience can be highlighted as potential targets for development assistance.

Climate change is affecting the frequency and intensity of weather hazards, and there is a growing interest in defining metrics related to the ability to adapt to these changes. Combining new hazard scenarios with our socioeconomic resilience can be one of the building blocks of an indicator of climate change resilience (Engle et al., 2013). Finally, many of the countries that are likely to be the most vulnerable to climate change are also those where data are lacking. Producing an exhaustive map of socioeconomic resilience would require data collection in these countries or developing a reduced, less data intensive, version of the model presented here (for instance based only on the parameters identified in Figures 6 to 8).

Our approach adds to the literature and existing indicators because (1) it is based on a formal theoretical framework and on a formal and quantified definition of resilience (the ratio of asset and welfare losses); (2) it adds a focus on the poorest and most vulnerable by distinguishing between the characteristics of the poorest 20 percent and the rest of the population; and (3) it provides an associated tool to assess the benefits from various risk management policies, such as adaptive social protection or early warning systems.

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Appendix. PAGER building categories aggregated into three general categories to representing differential vulnerability.

Agg. Cat.	PAGER building category	Vuln.
Fragile	Adobe blocks (unbaked sundried mud block) walls Adobe block, mud mortar, wood roof and floors Adobe block, mud mortar, bamboo, straw, and thatch roof; A block, straw, and thatch roof cement-sand mortar; Adobe block, mud mortar, reinforced concrete bond beam, cane and mud roof; Adobe block, mud mortar bamboo or rope reinforcement; Rectangular cut-stone masonry block; Rectangular cut stone masonry block with mud mortar, timber roof and floors; Inf constructions; Mud walls; Mud walls without horizontal wood elements; Mud walls with horizontal wood elements; Mobile homes; Rubble stone (field s masonry; Local field stones dry stacked (no mortar) with timber floors, earth, or metal roof; Local field stones with mud mortar; Local field stones with lime m Local field stones with cement mortar, vaulted brick roof and floors; Unreinforced fired brick masonry; Unreinforced brick masonry in mud mortar without t posts; Unreinforced brick masonry in mud mortar with timber posts; Wood light unbraced post and beam frame; Wood panel or log construction; Wattle and (Walls with bamboo/light timber log/reed mesh and post); Wood unbraced heavy post and beam frame with mud or other infill material; Wood braced frame load-bearing infill wall system	70%
Median	Rectangular cut stone masonry block with lime mortar; Rectangular cut stone masonry block with cement mortar; Local field stones with cement mortar a reinforced concrete bond beam; Ductile reinforced concrete moment frame with or without infill low-rise; Reinforced concrete shear walls low-rise; Nonduc reinforced concrete frame with masonry infill walls low-rise; Nonductile reinforced concrete frame without masonry infill walls low-rise; Steel reinforced concr (Steel members encased in reinforced concrete) low-rise; Concrete moment resisting frame with shear wall - dual system low-rise; Rectangular cut stone maso block with reinforced concrete floors and roof; Massive stone masonry in lime or cement mortar; Precast concrete frames with concrete shear walls low-r Precast reinforced concrete moment resisting frame with masonry infill walls low-rise; Rammed Earth/Pneumatically impacted stabilized earth; Concrete bl unreinforced masonry with lime or cement mortar; Unreinforced brick masonry in lime mortar; Unreinforced fired brick masonry, cement mortar; Unreinfor fired brick masonry, cement mortar, but with reinforced concrete floor and roof slabs; Not specified (unknown/default); Wood; Wood stud-wall frame w plywood/gypsum board sheathing; Wood frame, heavy members (with area > 5000 sq. ft.)	30%
Rosbust	Reinforced concrete; Ductile reinforced concrete moment frame with or without infill; Ductile reinforced concrete moment frame with or without infill high-r Ductile reinforced concrete moment frame with or without infill mid-rise; Reinforced concrete shear walls; Reinforced concrete shear walls high-rise; Reinfor concrete shear walls mid-rise; Nonductile reinforced concrete frame with masonry infill walls; Nonductile reinforced concrete frame with masonry infill walls hi rise; Nonductile reinforced concrete frame with masonry infill walls mid-rise; Nonductile reinforced concrete frame without masonry infill walls; Nonduc reinforced concrete frame without masonry infill walls high-rise; Nonductile reinforced concrete frame without masonry infill walls mid-rise; Steel reinfor concrete (Steel members encased in reinforced concrete); Steel reinforced concrete (Steel members encased in reinforced concrete) high-rise; Steel reinfor concrete (Steel members encased in reinforced concrete) mid-rise; Concrete moment resisting frame with shear wall - dual system; Concrete moment resist frame with shear wall - dual system high-rise; Concrete moment resisting frame with shear wall - dual system mid-rise; Flat slab structure; Confined masor Confined masonry high-rise; Confined masonry low-rise; Confined masonry mid-rise; Precast concrete tilt-up walls; Precast concrete frames with concrete sh walls; Precast concrete frames with concrete shear walls high-rise; Precast concrete frames with concrete shear walls mid-rise; Precast reinforced concr moment resisting frame with masonry infill walls; Precast reinforced concrete moment resisting frame with masonry infill walls high-rise; Precast reinfor concrete moment resisting frame with masonry infill walls mid-rise; Precast panels (wall made of number of horizontal precast panels, construction from forr Soviet Union countries); Reinforced masonry; Reinforced masonry bearing walls with wood or metal deck diaphragms; Reinforced masonry bearing walls w wood or metal deck diaphragms low-rise; Reinforced masonry bearing walls with wood or metal deck diaphragms mid-rise (4+ stories); Reinforced masonry bea walls with concrete diaphragms; Reinforced masonry bearing walls with concrete diaphragms high-rise; Reinforced masonry bearing walls with concr diaphragms low-rise; Reinforced masonry bearing walls with concrete diaphragms mid-rise; Steel; Steel moment frame; Steel moment frame high-rise; St moment frame low-rise; Steel moment frame mid-rise; Steel braced frame; Steel braced frame high-rise; Steel braced frame low-rise; Steel braced frame mid-r Steel light frame; Steel frame with cast-in-place concrete shear walls; Steel frame with cast-in-place concrete shear walls high-rise; Steel frame with cast-in-pl concrete shear walls low-rise; Steel frame with cast-in-place concrete shear walls mid-rise; Steel frame with unreinforced masonry infill walls; Steel frame w unreinforced masonry infill walls high-rise; Steel frame with unreinforced masonry infill walls low-rise; Steel frame with unreinforced masonry infill walls mid-	10%