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Assessing Socioeconomic Resilience to Floods in 90 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, and a tool to help decision makers identify the most promising policy options to reduce welfare losses due to floods. Calibrated with household surveys, the model suggests that welfare losses from the July 2005 floods in Mumbai were almost double the asset losses, because losses were concentrated on poor and vulnerable populations. Applied to river floods in 90 countries, the model provides estimates of country-level socioeconomic resilience. Because floods disproportionally affect poor people, each $1 of global flood asset loss is equivalent to a $1.6 reduction in the affected country's national income, on average. The model also assesses and ranks policy levers to reduce flood 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 benefits. And some policies, such as adaptive social protection, do not reduce asset losses, but still reduce welfare losses. Asset and welfare losses can even move in opposite directions: increasing by one percentage point the share of income of the bottom 20 percent in the 90 countries would increase asset losses by 0.6 percent, since more wealth would be at risk. But it would also reduce the impact of income losses on wellbeing, and ultimately reduce welfare losses by 3.4 percent.

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Introduction

The most immediate consequences of floods 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 propose an approach and a model to support this process. In this work-in-progress, we combine data on flood hazard, population and asset location, asset vulnerability, and socioeconomic characteristics and combine insights from natural and social sciences to assess how floods affect wellbeing, measured using a *social welfare function* (*welfare* is the metric used by economists to measure wellbeing). We present the model using a case study – the 2005 floods in Mumbai, India, for which macro- and micro-economic data are available. We then use the model to define and assess the socioeconomic resilience of 90 countries to river floods, identify policy priorities to reduce the impact of floods on wellbeing, and help design holistic risk management strategies tailored to each country.

An Online Technical Note provides all the equations and technical details of the model, sensitivity analysis to show the robustness of the approach, and a comparison with other indicators for resilience or vulnerability. The model and the data are also 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 welfare – measured through the expected welfare losses due to floods – along with the three usual drivers, hazard

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

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

(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):

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

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 90 countries. 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 (or even increased) amount of asset losses. For instance, increasing by one percentage point the share of income of the bottom 20 percent in the 90 countries would increase asset losses by 0.6%, since more wealth would be at risk. But it would also reduce the impact of income losses on wellbeing, and ultimately reduce welfare losses by 3.4%. This finding suggests 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 use the model to rank a set of policy levers in 90 countries, according to their country-specific efficacy to reduce risk to welfare through its four drivers. We display this information using country-level *scorecards*, which describe each country with a set of sub-indicators (such as protection level, access to early warning, and social protection for poor and non-poor people) and report how improving each sub-indicator would impact risk (and resilience) for that country. (In contrast, existing indicators for resilience, risk, or vulnerability attribute the same weights to each sub-indicator in every country; see the Online Technical Note.) We find for instance that social safety nets are more important in countries with weak physical protection against floods, or high asset vulnerability. Our scorecards provide 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). They 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.

From asset losses to welfare losses

This section uses the July 2005 floods in Mumbai, India, to describe the model used to link asset losses from a natural disaster to welfare losses (Figure 1). The Online Technical Note provides all equations with detailed explanations, the full code and data. It also reports a sensitivity analysis on some of the model's most important assumptions, showing the robustness of the results.

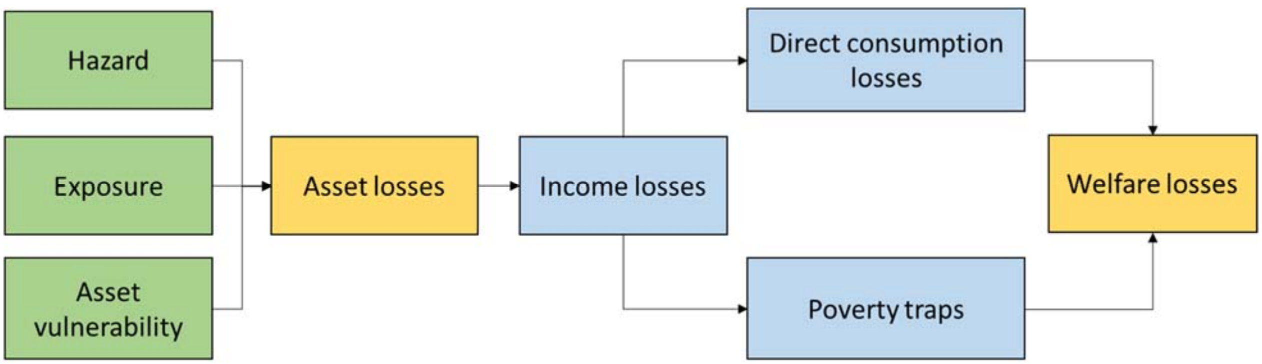


Figure 1: Schematic view of the model, from the drivers of asset losses to welfare losses. Calculations are done separately for poor and non-poor people.

The 2005 floods in Mumbai affected 4.2 million people and Rs. 350 billion in assets, causing Rs. 35 billion in damages (Ranger et al., 2011). We use standard economics to estimate consumption losses resulting from asset losses as a function of (i) how asset losses translate into income losses in the immediate aftermath of the disaster and (ii) the speed of recovery and reconstruction and associated expenditures (Figure 2).

We estimate output losses at the time of the shock as the product of the average productivity of capital multiplied by the amount of capital losses (we do not sum asset and output losses to avoid double-counting). This assumption reflects the fact that natural disasters destroy existing capital randomly, and that the remaining capital cannot be re-allocated instantaneously to its most productive use (Online Technical Note and Hallegatte, 2014; Hallegatte et al., 2007). It is a simplification of a complex reality, and multiple economic, technical, and institutional characteristics can magnify or reduce the instantaneous decrease in economic output (Henriet et al., 2012; Noy, 2009; Rose and Krausmann, 2013). We also assume that economies return to their pre-disaster situation, disregarding the possibility to "build back better." This latter assumption tends to over-estimate economic costs, but makes it possible to compare the economic situation after the disaster against a simple counterfactual: a stable economy with no disaster.

With these assumptions, the discounted value of the lost consumption is $\widetilde{\Delta C} = \Delta K(\mu + 3/N)/(\rho + 3/N)$, where ΔK is the value of the damages to assets, μ is the average productivity of capital, N is the reconstruction period duration (until 95% of damages are repaired), and ρ is the discount rate. The total value of output losses is thus larger than the pre-disaster value of the lost capital.

In Mumbai, reconstruction took place over 18 months (Ranger et al., 2011), leading to an estimated Rs. 39 billion of discounted consumption losses.

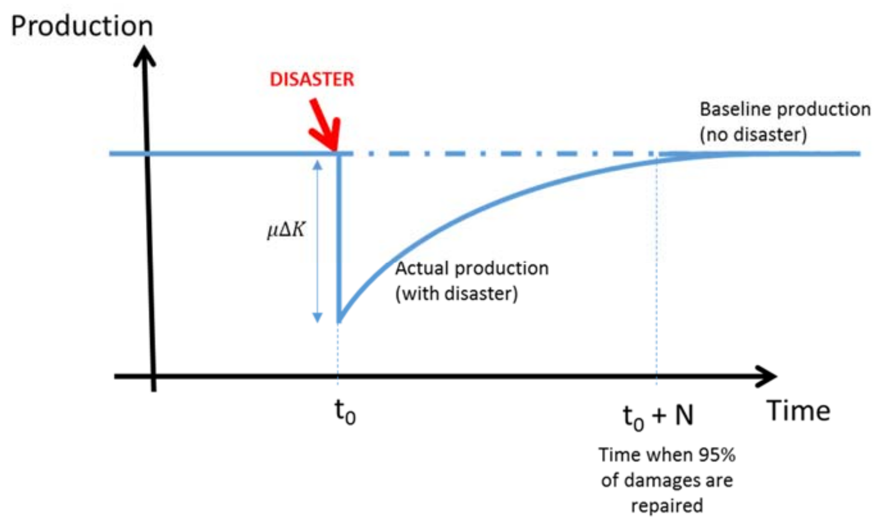


Figure 2: Schematic view of the economic output dynamics. The variable μ is the average productivity of capital and N is the reconstruction period duration (until 95% of damages are repaired).

The same aggregate consumption loss has a higher impact on wellbeing if it disproportionally affects a small fraction of the population, and especially if it affects people close to the subsistence level. Analyses of household location and flood hazard show that poor households (with income less than Rs. 5,000 per month) were 71% more likely to have been flooded than the average household (Patankar and Patwardhan, 2014). We call this the *exposure bias*. Similar biases have been found in many other disaster situations (Brouwer et al., 2007), but not everywhere (Carter et al., 2007; Hallegatte et al., 2016b). We also use an *asset-vulnerability bias* to measure the difference in the magnitude of asset losses when a poor or a non-poor person is flooded. In Mumbai, household surveys show that poor people lost approximately 60% more than non-poor people, relative to their estimated wealth (Patankar and Patwardhan, 2014). This *vulnerability bias* is confirmed in all post-disaster case studies we are aware of (Hallegatte et al., 2016b).

For a given individual, poor or nonpoor, how asset losses translate into income losses depends on the diversification of his or her livelihood and income, and the ability and options to respond to the shock (Barrett et al., 2001). To approximate diversification, we differentiate income from labor and income from transfers (from social protection, pensions, and remittances). We assume income from labor decreases in proportion to each individual's asset losses. In contrast, we assume transfers such as pensions are diversified at the country level (e.g., through the government budgets or the financial system) and decrease in proportion to national asset losses. As a result, higher diversification leads to lower income losses, as long as losses at national scale remain small (Figure 3).[3] In Mumbai, diversification is estimated at 10% of income, and, since the fraction of people affected in Mumbai is negligible given the scale of India, income from transfers is largely unaffected by the floods.

We also account for the response to the disaster, and especially for formal and informal insurance (Kunreuther et al., 1978; Skoufias, 2003), remittances (Le De et al., 2013), and ad-hoc post-disaster transfers and the scaling-up of social protection (Siegel and de la Fuente, 2010). These mechanisms can replace some of the lost income after a disaster and reduce resulting consumption losses. Case studies suggest they can be very effective at reducing welfare losses from natural disasters (Hallegatte et al., 2016a). In Mumbai, insurance is largely absent, but the government provided post-disaster support to households, amounting to approximately 10% of their asset losses.

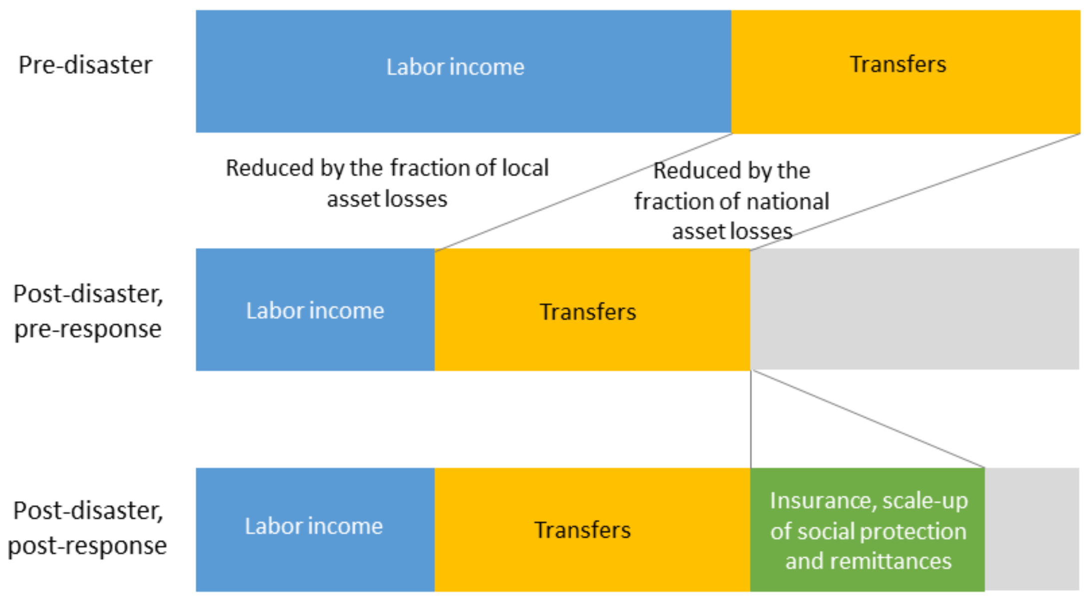


Figure 3: Income of one category (poor or non-poor) in one country or one city, before the disaster, after the disaster but before the response to the disaster, and after the disaster and the response.

Based on our assumptions on how asset losses translate into income losses, and household-level data on diversification and post-disaster support, our model suggests that income loss at the time of the flood was around 11% and 8% for poor and non-poor affected people, respectively. Household surveys focusing on post-flood income provide results that are consistent with this modeling (Patankar and Patwardhan, 2014).

We translate consumption losses into welfare losses using a classical welfare (or utility) function, reflecting that the same dollar amount of consumption loss causes higher wellbeing losses to poor than

[3] Sometimes losses at national level are not negligible: for instance the island of Grenada lost 200% of its GDP to Hurricane Ivan in 2004. In these cases, diversification at the national level is less effective at mitigating income losses.

to nonpoor people. The *elasticity of the marginal utility of consumption* is the parameter that describes how $1 in consumption loss affects differently poor and non-poor people. Implicitly, it sets *distributional weights*, i.e. the weight attributed to poor people vs. the rest of the population in the aggregation of costs and benefits in an economic analysis (Fleurbaey and Hammond, 2004). We use a standard value of 1.5 but, as this parameter is a normative choice, we explore in the Online Technical Note how results change for different values. Higher values give more importance to poor people, lead to higher estimates of welfare losses, and make it relatively more important to use policy instruments targeted towards poor people to reduce welfare risks at the country-level.

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*. In Mumbai, 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. 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.[4]

To account for these effects, we calculate the number of people with very low post-disaster, post-response consumption and assume that a fraction of them are unable to fulfill their basic needs and suffer from losses that go beyond the impact of a change in aggregate consumption. We count individuals with income levels below a threshold equal to 10% of average GDP per capita in the country. Of those with very low income levels, we exclude households who save at a financial institution, assuming that these savings allow smoothing the shock (through dissaving or borrowing to smooth the shock). Finally, we also exclude those who are assumed protected by the socioeconomic environment. We assume that in a country where healthcare is available and affordable, where children attend school at least until the end of primary school, and where unemployment is low, people are less likely to fall into poverty traps. In the absence of a full model for these effects, we assume that the fraction of people falling into poverty traps is inversely proportional to a simple indicator that averages measures of access to health, access to education, and employment (see the Online Technical Note).

People who have very low income and are not protected by their own savings or the socioeconomic environment are assumed to fall into a poverty trap (or to transmit poverty to their children), leading to an additional welfare loss. This welfare loss is estimated to be equal to the discounted value of the loss of the average individual's income in the country, returning to normal over 40 years (one generation). This is of course a crude simplification of reality – which consists of a continuum of intertwined impacts on

[4] (Barrett and Constas, 2014) propose a definition of *development resilience* that focuses on the capacity of people to avoid such poverty traps.

wealth and instantaneous consumption – but it allows including in the calculation in a simple way an essential component of disaster impacts. In Mumbai, we find that very few people (5,000 or 0.002% of the population) are at risk of poverty traps, although the impact is large for those affected.

We estimate welfare losses due to the 2005 flood in Mumbai around Rs. 60 billion, almost twice as large as asset losses, resulting in a socioeconomic resilience of the city of 57%. The main reasons for large welfare consequences are the over-exposure and over-vulnerability of poor people (poverty traps explain only 0.5% percent of these welfare losses).

We then assess policy options to reduce welfare losses from floods in Mumbai (Figure 4). Some policies reduce welfare losses *by* reducing asset losses (e.g., flood zoning, improving asset quality). Other options (increasing post-disaster support, accelerating reconstruction, reducing vulnerability bias, increasing diversification, or improving access to savings) reduce welfare losses from unchanged asset losses. And some policies (reducing poverty) increase total asset losses, but increase socioeconomic resilience even more, and thus ultimately reduce welfare losses.

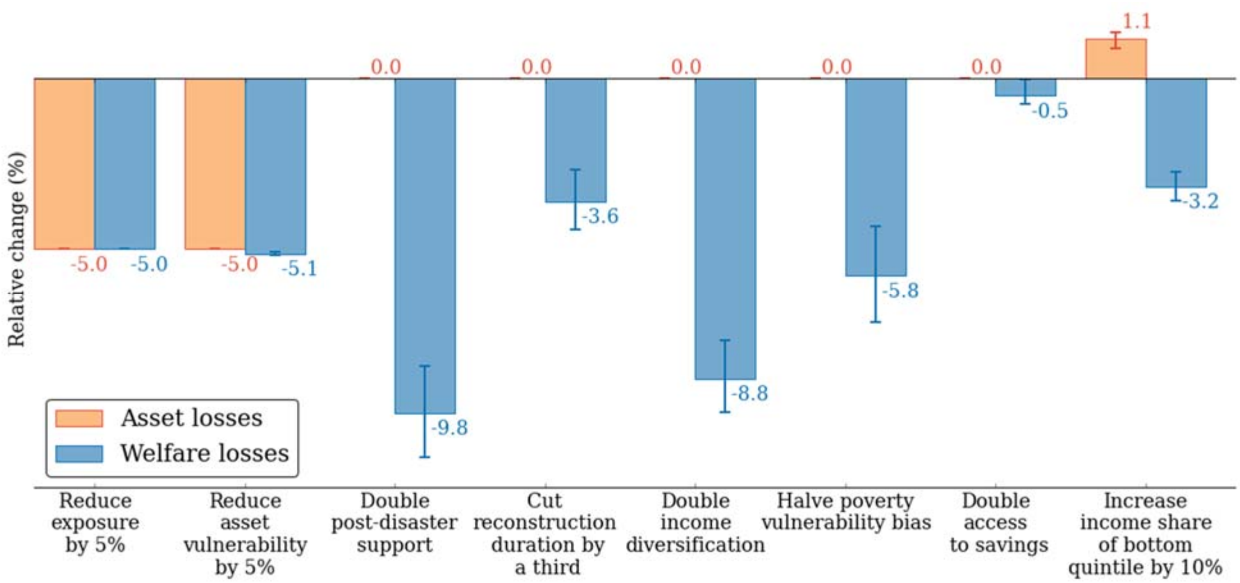


Figure 4: How asset and welfare losses of the 2005 floods in Mumbai could have been different – a look at the potential impact of different policy measures. Reducing poverty (right-most option) increases asset losses but reduces welfare losses, as it increases the ability of poor people to cope with asset losses. Error bars represent the interquartile interval of the sensitivity analysis (see text).

These findings provide the first quantification of the wedge between asset and welfare losses, and make it possible to investigate the drivers of this wedge. For instance, it is well-accepted that rapid reconstruction is critical to reduce disaster welfare impacts; we quantify this fact for the first time: in Mumbai, cutting reconstruction duration by a third would reduce welfare losses by 3.6%. Such quantification is a useful input for a cost-benefit analysis, and allows comparison with other policy measures. Similarly, income diversification, social protection and insurance are widely discussed as potential tools to increase resilience (G7, 2015; Hallegatte et al., 2016c; Surminski et al., 2016), and we provide here an indication of the benefits from these tools, making it possible to compare them with implementation costs and alternative approaches such as land-use planning or building retrofitting.

Regarding poverty, these results indicate that there is no trade-off between poverty reduction and risk management. Even if poverty is reduced without improving the exposure or asset vulnerability to floods, thus increasing asset losses when disasters hit (by 1.1% in our model), the net effect on welfare is positive (losses are reduced by 3.2%) due to the increased ability of poor people to cope with asset losses. This is an important finding, for example for city managers who may worry that better living standards and higher-value buildings increase asset risks: while they do, wellbeing risks are ultimately reduced.

To account for the uncertainty in the exposure to the flood and its consequences and in socioeconomic characteristics (e.g., diversification), we perform a systematic sensitivity analysis by varying all uncertain parameters 33% above and below their central value, and measure the robustness of our findings (see the Online Technical Note for full details). Error bars in Figure 4 report the resulting interquartile uncertainty on the impacts of the various policies on asset and welfare losses. It shows our results to be robust. We find also that the relative ranking of the policies is stable and not sensitive to the uncertainties. Additionally, we explore changes in the elasticity of the marginal utility of consumption, which is a normative choice, not an uncertainty. We find that it affects only the magnitude of the benefits from reducing poverty or the exposure bias, but it does not affect our qualitative results and the ranking of policy options.

Improving socioeconomic resilience to floods in 90 countries

We use this model to quantify socioeconomic resilience in 90 countries and assess how different policy options can improve resilience and reduce the welfare impacts of river floods. Since we cannot rely on ex-post observation and household surveys to calibrate the model, we use proxies and national-level data. Also, we do not calculate the resilience for one event – like for Mumbai in 2005 – but the resilience to many possible flood events. We calculate asset and welfare losses for several return periods (between 5 and 1,000 years) and estimate the socioeconomic resilience as the ratio of expected asset losses to expected welfare losses. A complete description of the model is available in the Online Technical Note.

Hazard is represented by a flood's probability of occurrence, above the level of protection provided by embankments and artificial dikes. In each country, we set to zero the exposure to all events with a return period equal or lower than the protection level. We calibrate the protection level by country using the global open and collaborative database FLOPROS (Scussolini et al., 2015). FLORPOS provides estimates at the sub-national level based on expert estimates of *de facto* protection if available, *de jure* legislation and performance standards otherwise, or simple economic modeling if both de facto and de jure data are lacking.

Above the protection level, population and asset exposure to floods is estimated using GLOFRIS, a global river flood model (Jongman et al., 2015, Jongman et al., 2012). This model provides gridded flood inundation estimates at the 1km^2 resolution for 9 return periods (from 5 to 1000 years), all countries, and in all large river basins. The model does not include all floods: coastal floods are not taken into account, and flash floods and small river basins have not been represented in a global model at this stage. These flood maps are overlaid with a global population density data set, Landscan (Geographic Information Science and Technology, 2015) to estimate the percentage of the population exposed to floods in each country, river basin, and for each return period.

An important complication is the difference between the exposure to a flood in a basin for a given return period (say, the 100-year flood), and the number of people that are affected in the country *at once*: while 2.1 percent of Brazil's population is exposed to a 100-year event in our simulations, this population is distributed in many river basins that will not flood at the same time. Here, we make the simplifying assumption that river basins in each country are independent, neglecting cross-basin correlation (Jongman et al., 2014), and we perform a Monte Carlo analysis to derive exposure in a country at a given return period by aggregating simulations at the basin level.

We use estimations of the exposure bias published by the World Bank (Hallegatte et al., 2016a). The World Bank study overlays the same GLOFRIS flood maps with geo-localized household surveys (from the Demographic and Health Survey) to assess the exposure of poor people relative to the exposure of non-poor people within 52 countries. Countries where data are not available are attributed the average exposure bias.

We proxy asset vulnerability and the asset-vulnerability bias using a global data set of building types (USGS PAGER). We classify buildings in three categories (low, medium, and high quality), which we match to simple damage-depth functions (Hallegatte et al., 2013), and we assume richer households live in and use higher quality assets. What fraction of assets is lost to a disaster also depends on softer measures, such as the existence of early warning systems. In addition to being an effective way of reducing casualties and fatalities, early warning allows households to plan for a disaster, and move some of their assets outside (or above) the affected zone, thereby reducing asset losses (Hallegatte, 2012; Kreibich et al., 2005)**.** Based on previous case studies, we assume that asset losses are reduced by 20 percent when people have access to early warnings, and we use data from the Hyogo Framework for Action (HFA) monitoring system on early warning to estimate the fraction of population with such access.

For income diversification, social protection and financial inclusion, we build on global databases such as the Atlas for Social Protection – Indicators of Resilience and Equity (ASPIRE) and Global Financial Inclusion (FINDEX). Parameters related to the socioeconomic characteristics that modify risks of irreversible human capital losses – employment, healthcare, and education – are from the World Development Indicators (WDI).

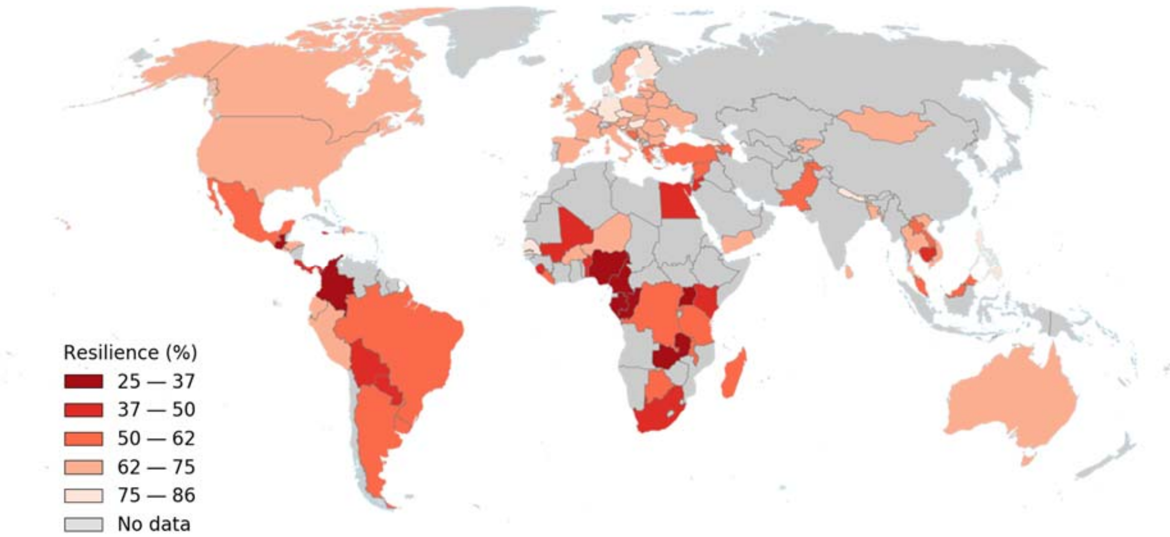
Adaptive social protection, where social protection benefits and/or beneficiaries is expanded automatically in the aftermath of a disaster, is an efficient tool to reduce the welfare impact of disasters (Davies et al., 2013; Hallegatte et al., 2016c). It is impossible to predict the support that will be provided after a disaster, so we assume a willingness to share the losses, and proxy for the ability to provide such support, depending on institutional capacity and public financial management. To measure countries' ability to manage public finance and reallocate resources in times of crisis, we use sovereign credit ratings. We use data from the HFA on contingent finance, the existence of plans for emergency response and social protection scale-up. More in-depth analyses of the post-disaster *financing gap* have been performed using specific models, investigating the various mechanisms available to finance post-disaster actions, including budget reallocation, domestic and international borrowing, and specific instruments such as catastrophe-bonds, insurance contracts, or reserve funds (Cardenas et al., 2007; Hochrainer-Stigler et al., 2014). In a next phase, results from these more sophisticated models can be used to refine our estimates of the ability of each country to fund crisis management and provide post-disaster support.

Our methodology to assess asset risk is a simplification of state-of-the-art catastrophe modeling (Aerts et al., 2014; Michel-Kerjan et al., 2013; UN-ISDR, 2015), applicable with global data. As a result, our estimates for flood probability, exposure and asset vulnerability have to be considered with caution. Our simplifications are acceptable as we focus on how asset losses translate into welfare losses (socioeconomic resilience), not specifically on asset losses. The sensitivity analysis presented in the Online Technical Note concludes that our estimates of socioeconomic resilience and our ranking of policy options are largely independent of aggregate asset exposure and vulnerability. Our main results are thus robust to the simplicity of the hydrological modeling and to errors in exposure and asset vulnerability data.

We assess the resilience of 90 countries to floods, by calculating the ratio of expected asset losses to expected welfare losses. Resilience averages 61% across our sample, ranging from 25% to 86%. Resilience in Malawi is 53%, which means that $1 of asset losses in Malawi has the same impact on welfare as a reduction of Malawi’s national income by almost $2.[5] All 90 countries are represented in Map 1, and the list of countries with their risk and resilience information is in the Appendix below. Risk to wellbeing (expected welfare losses in percent of GDP) decreases rapidly with income per capita (Figure 5a), mostly due to better protection and lower asset vulnerability.

High-income countries also tend to have higher resilience (Figure 5b), but resilience has a large variance even when GDP per capita is controlled for, especially at low income levels. Resilience varies across countries of similar wealth because welfare consequences depend on a multitude of factors, including pre-existing inequality and safety nets to reduce the instantaneous 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.

[5] Our measure of socioeconomic resilience does not include the fact that a reduction of national income by $2 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.



Map 1: Socioeconomic resilience in the 90 countries.

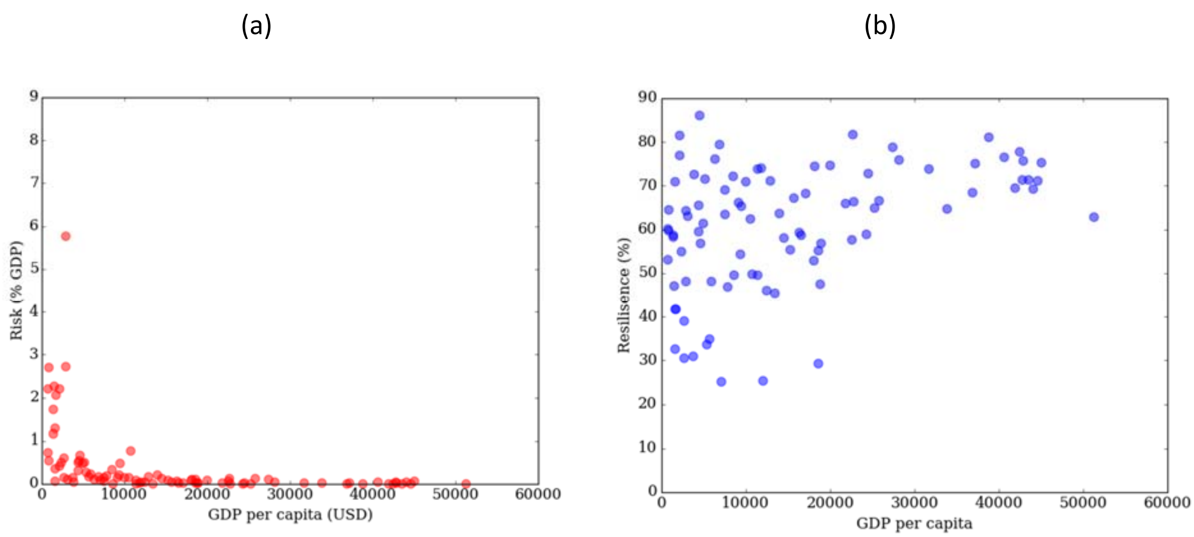


Figure 5: Risk to welfare (a) and resilience (b), plotted against income level.

The lowest socioeconomic resilience in our sample is Guatemala, at 25% (i.e. $1 in flood 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 (321%, the largest in the sample), and a relatively low level of social protection and access to finance, for the poor and non-poor, making them vulnerable to poverty traps. And the socioeconomic environment is not very supportive, with the low values of the proxies for education and even more for access to health.

The highest resilience is Moldova, with 86 percent (i.e. welfare losses are only 16% larger than asset losses). This high resilience is mostly due to very low exposure bias (at -52%, poor people experience twice less frequent floods than nonpoor people), low inequality (the income share of the bottom 20 percent is 8.5 percent, among the highest in our sample), large transfers from social protection, and the strong socioeconomic environment. It does not mean that the risk to welfare is particularly low, however. Due to a low protection level, annual welfare losses reach almost 1% of GDP in our analysis.

Interestingly, resilience is only weakly correlated to exposure (0.23) and risk (-0.18). This is because many drivers of resilience are socioeconomic conditions that are outside the domain of traditional disaster risk management, focused on asset losses. It seems obvious that no country ever decided to reduce income inequality because of a high exposure to natural hazards, even though inequality is a major driver of our resilience indicator.

Reducing poverty reduces welfare losses from floods in all 90 countries. Increasing the wealth of poor people increases total asset losses, but increases even more the ability of poor people to cope with those asset losses. This result may remind the widely accepted fact that richer countries tend be more resilient than poorer ones; while richer countries experience larger economic losses, they suffer fewer casualties and fatalities than poorer countries (Guha-Sapir et al., 2013; Kahn, 2005). But this result is different: our analysis investigates welfare losses – not casualties or asset losses – and accounts for the distribution of losses and resources *within* – not across – countries.

Main drivers of risk and resilience

To identify the parameters which best explain differences in resilience, we conduct a simple sensitivity analysis. For each input parameter (exposure, income share of bottom quintile, etc.), we estimate the risk to assets, risk to welfare, and socioeconomic resilience if we did not know that parameter: that is, we change that parameter value in all countries to its average across countries. We then compare these estimates to the original ones computed with the original parameter values, and we call *error* the average of the relative difference (Figures 6-8). A large error means that knowing the value of the parameter is important, either because the model is sensitive to it, or because the actual values vary widely across countries. A small error means that the parameter is not that important when estimating resilience, and disregarding it in the analysis would lead to similar results.

For the risk to assets, figure 6, the most important parameters are population exposure, protection, and asset vulnerability. If these parameters are wrong, the estimate of the risk to asset is also wrong. We find here the three usual components (hazard, exposure, and vulnerability). For instance, replacing exposure in all countries with the average exposure across countries (5.1% of the population) would result in an average 180% error in the estimate of risk to assets on average. The other parameters also enter the calculation: for instance, the productivity of capital and the exposure bias is used to translate population exposure into an exposure expressed in asset value. Access to early warning has an impact as it decreases effective capital vulnerability.

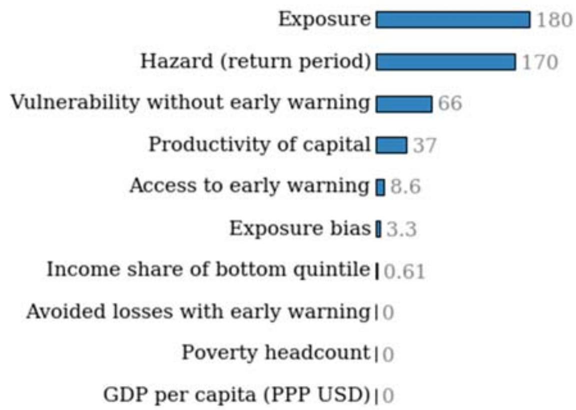


Figure 6: Main drivers of the risk to assets. This figure shows the mean relative error in the assessment of the risk to asset if the country values for these parameters are replaced by the average across countries.

For socioeconomic resilience, figure 7, we find that the productivity of capital is important because it has a large variance – it varies by a factor 4 among countries, especially among low-income countries. Higher productivity of capital tends to increase socioeconomic resilience: the small quantity of capital (compared to GDP) makes the reconstruction process faster and easier, and thus reduces welfare losses from a given level of asset losses. This factor tends to increase the resilience of poor countries that have a high productivity of capital – a result of capital scarcity – this factor tends to increase their resilience.[6]

All the other major factors are linked to inequality. They include exposure bias (that measures the localization of poor vs. non-poor people and the land markets and regulations), asset-vulnerability bias (linked to the type and quality of asset of poor vs. non-poor people), income inequality (i.e. the share of income of the bottom 20 percent), and the amount of social protection available for poor people. This analysis suggests that a reduced-form model with only 5 parameters could provide a relatively accurate estimate of socioeconomic resilience.

[6] This finding is consistent with evidence suggesting that low-income economy can return to normalcy relatively quickly, even after large shocks (Albala-Bertrand, 2013; Kocornik-Mina et al., 2015; Ranger et al., 2011). Because economic production relies on little capital, indeed, reconstruction per se can be extremely quick. Note that long-term impacts in low-income environments seem more often linked to impacts on human capital, i.e. to fatalities, casualties, heath impacts, lost education, or trauma, or on conflicts and governance, more than on physical capital.

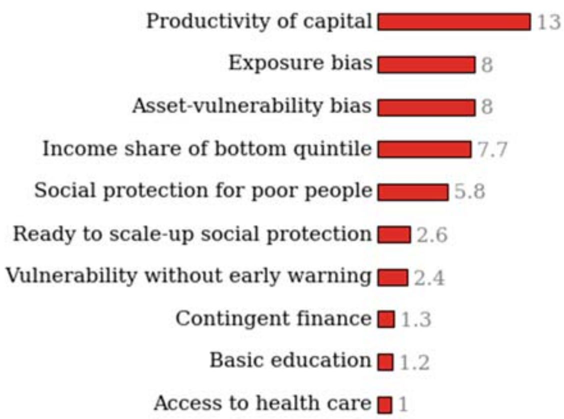


Figure 7: Main drivers of resilience. This figure shows the mean relative error in the assessment of socioeconomic resilience if the country values for these parameters are replaced by the average across countries.

The drivers of the risk to welfare, figure 8, are a composite of those of the risk to assets and those of resilience, and more parameters are needed to provide a reasonable estimate of the risk to welfare. Population exposure, protection level, and vulnerability appear first, but inequality characteristics also matter, such as the asset-vulnerability and exposure biases or the income share of the bottom 20 percent.

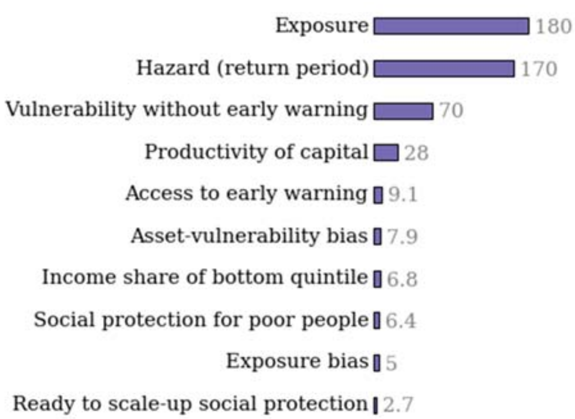


Figure 8: Main drivers of the risk to welfare. This figure shows the mean relative error in the assessment of the risk to welfare if the country values for these parameters are replaced by the average across countries.

How important are poverty traps for the calculation of resilience? Figure 9 plots resilience against GDP per capita, with and without accounting for the poverty trap calculation. It shows that poverty traps play a relatively minor role in our assessment of the consequences of floods. Unsurprisingly, they matter only in poor countries, where a large share of the population has no access to savings for smoothing shocks, the government has a harder time absorbing part of the losses through adaptive social protection, and institutional conditions favor poverty traps. In particular, lack of access to health care (because of supply or affordability issues) and low primary school completion rates suggest that children are particularly vulnerable in these countries. In low-income countries, the difference in resilience with and without poverty traps can exceed 5 percentage points. This result suggests that the complexity in our model linked to the poverty traps could be removed at the expense of an overestimation of resilience in low-income countries.

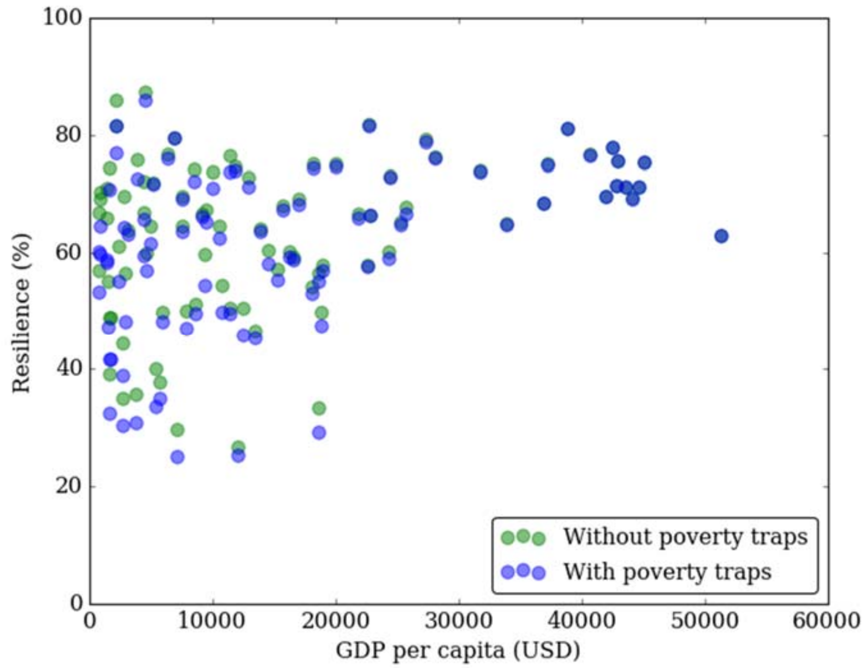


Figure 9: The resilience of the 90 countries, with and without accounting for poverty traps.

Disaster Management Scorecards

We now use the model to assess how much different policy actions can increase resilience and reduce welfare losses in each country. To communicate this information, we propose *disaster management scorecards*, shown in Figure 10 for Malawi (all 90 scorecards are available in the Online Technical Note). The scorecard shows that Malawi has one of the highest flood risks in the world, with risk (expected welfare losses from river floods) estimated at 1.2% of GDP. Then, the scorecard describes the four drivers of risk: hazard (using protection level), exposure, asset vulnerability, and resilience.

The scorecard shows the change in each of the drivers required to reduce risk by 10% (from 1.2% to 1.1% of GDP). These values are calculated by running the model with incremental changes in each of the drivers, to assess their efficacy to reduce welfare impacts from a flood. In Malawi, reducing risk by 10% would require increasing the protection level from a 3 to a 3.15-year return-period event, decreasing exposure by 0.23 percentage points, reducing asset vulnerability by 3 percentage points, *or* increasing resilience by 5.3 percentage points. How could such changes in asset vulnerability or resilience be achieved? The scorecard breaks down asset vulnerability and resilience into several sub-indicators. It also reports how much each sub-indicator needs to change to reduce asset vulnerability or improve resilience by the required amount (right-most column, also based on model runs with small changes in parameters).

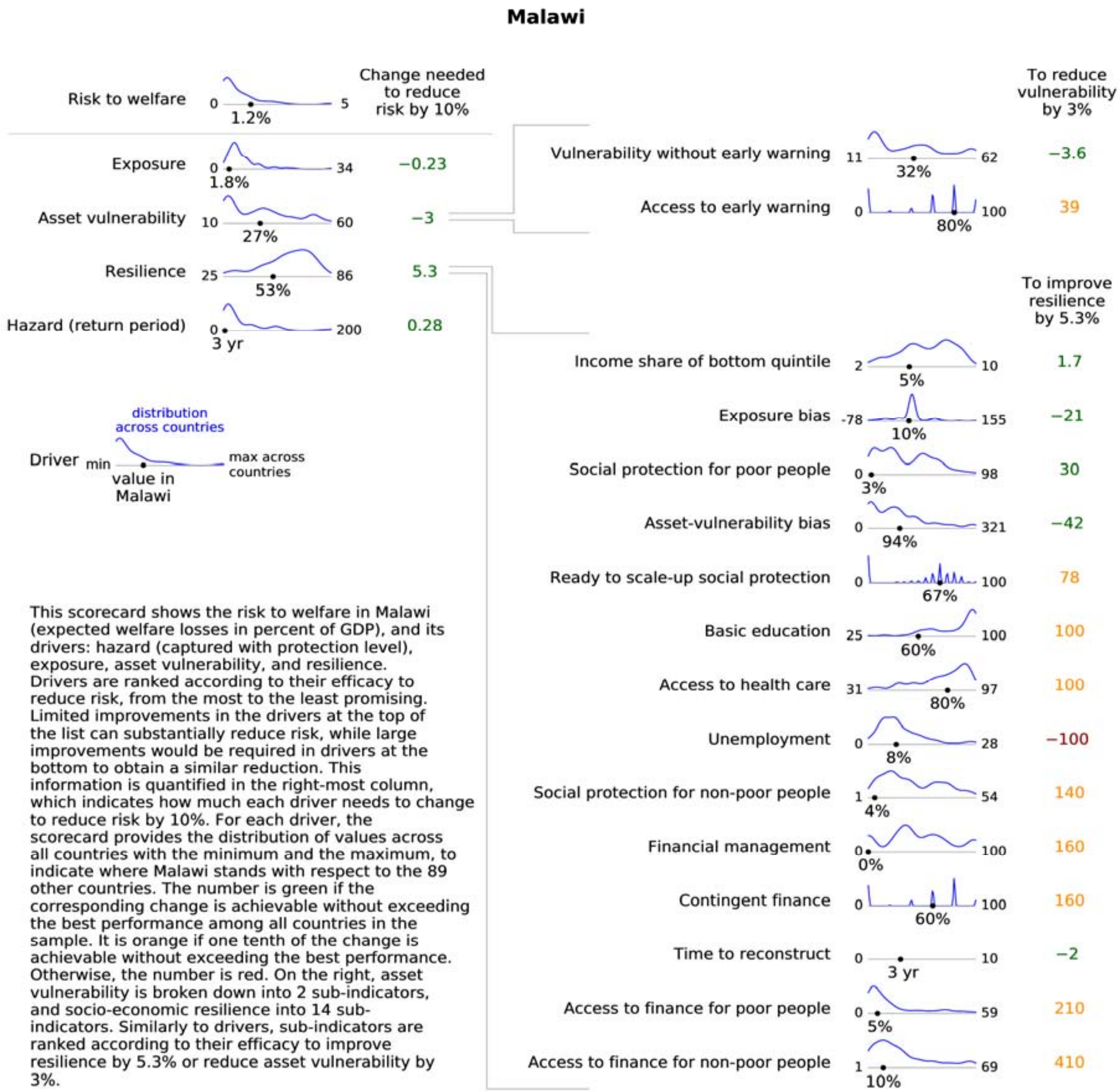


Figure 10: Disaster management scorecard for river floods in Malawi.

Asset vulnerability depends on asset vulnerability without early warning, and on access to early warning – which reduces asset losses. Resilience depends on 14 sub-indicators that describe the relative distribution of exposure and asset vulnerability in the population and the socioeconomic context (e.g., regarding social protection). The scorecard provides some insights into policy options to improve resilience in the country.

The most efficient policy action to increase resilience in Malawi is to reduce poverty. Increasing the share of income earned by the bottom 20% by 1.7 points (a realistic increase) would increase resilience by 5.3 points. The third sub-indicator is also poverty-related and measures the targeting of social protection to poor people. Social protection provides only 3% of total income for poor people in Malawi, one of the lowest values of the sample. An increase from 3 to 33% – an ambitious but not unattainable change – would also increase resilience by 5.3 points (and thus reduce risk by 10%). Since these two sub-indicators are effective and areas in which the country is lagging, they are obvious candidates to increase resilience. Further, such policies may be development priorities, irrespective of flood risk.

The second lever is exposure bias. Poor people in Malawi are 10% more likely to be exposed to floods than non-poor people. Bringing this value to -11%, so that poor people are *less* likely than the average to be affected, would increase resilience by 5.3%. Asset quality also matters: reducing the excess vulnerability of poor people's assets (vs. the rest of population) from 94 to 52% increases resilience by 5.3 points. This could be done by better enforcing building norms, or by supporting access to higher-quality buildings for poor people.

In Figure 11, we show a similar scorecard for Sweden, where risk is much lower (at 0.03% of GDP), mostly because protection is much better. Resilience is also higher, at 71%. In Sweden, decreasing risk by 10% would require increasing resilience by 7.1 points, which would require increasing the income share of the bottom 20 percent by 6.5 points, from 10 to 16.5%, which would be unprecedented. Or it would take an increase in social protection towards poor people by 1800 points, which is impossible since it would then exceed 100%. Improving resilience in Sweden seems much more difficult than in Malawi, mostly because low-hanging fruits have already been captured. Only planning for faster reconstruction, protection investments, and policies to reduce exposure – especially for poor people – and reducing asset vulnerability appear promising.

Results are thus country-specific, which support the choice of using a model instead of a weighted average of sub-indicators, in which the weights are global and cannot be adjusted to local circumstances. The model allows for instance to identify specific situations:

- In countries where poor people have more vulnerable assets, it is particularly important to protect them with social protection instruments. This explains for instance why transfers to poor people is found a powerful policy lever in France (an increase by 21 point is enough to reduce risk by 10%, because the asset-vulnerability bias is 205%) while it is not efficient in Sweden (a 1800-point increase in social protection would be required, because the asset-vulnerability bias is only 1%). Germany is an intermediate case with an asset-vulnerability bias around 50% and where increasing social protection toward the poor by 64 points reduces risk by 10%.
- In countries where social safety nets are largely absent (e.g., Democratic Republic of Congo) many individuals lose everything from disasters and become dependent on education and health care services provided by the government and on good alternative employment opportunities – such policies appear high in the priority list.

In two countries, Hungary and Georgia, increasing the asset-vulnerability bias slightly increases resilience. This is because of relatively low inequalities and the very high level of protection provided by the social protection system to the poor (91% and 98%, respectively), compared with the support provided to the non-poor (53% and 54%, respectively). With such protection levels, it improves resilience to have more vulnerability concentrated on the poor, instead of the non-poor.

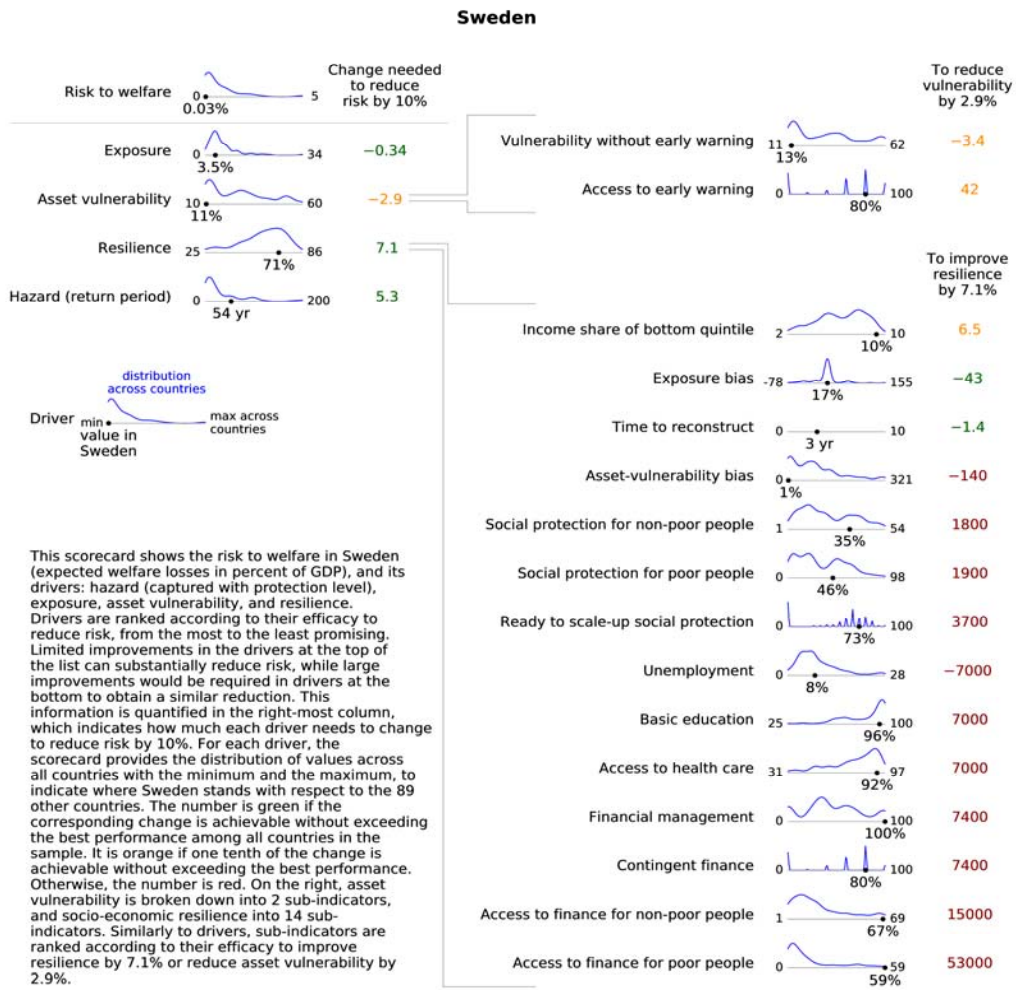


Figure 11: Risk management scorecard for Sweden.

As in the Mumbai case study, we ensure robustness of these findings to uncertain parameters, such as protection level, exposure and vulnerability to floods, the link between asset losses and income losses, income diversification, and the distribution of damages across affected households. The Online Technical Note provides a systematic sensitivity analysis to modeling assumptions and to the preference parameters. We find that the impact of policies (e.g. risk and resilience benefits) and their ranking are robust to these uncertainties. Here, again, normative choices matter: changes in the elasticity of the marginal utility of consumption affect the implicit weight given to poor and non-poor people, and thus the relative merits of poverty and poverty bias reduction.

Using the scorecards to assess policies

These scorecards do not provide definitive answers on which policies should be implemented. They provide an assessment of the resilience benefits from various policies. For instance, if a recovery fund can accelerate reconstruction by 10% or allow to scale-up social protection to compensate 25% of the losses, then the scorecard provides the resulting increase in resilience and decrease in risk. The socioeconomic resilience can also be used to translate in welfare terms the risk reduction benefits which are typically expressed in asset losses: if a new dike can reduce expected asset losses by $1 million per year in Malawi – with its 53 percent resilience – then welfare benefits can be estimated as equivalent to $2 million of additional consumption, assuming the dike protects the “average” population and is not biased toward non-poor people, for instance.

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 scorecards 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 88 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 maps 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.

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.

We have disregarded the impact on natural capital, in spite of its importance in the income of poor population 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 floods and other disasters.

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, 2014a) or explicit modelling 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.

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.

The assessment of physical risk used in this analysis focuses on river floods, but the analysis can be expanded to other hazards such as high winds, earthquakes, and droughts. Also, 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 is 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).

The Online Technical Note reviews other indicators that can usefully complement our approach with different methodologies or focuses (e.g., some methodologies give more weight to institutional factors; others accounts for community-level characteristics); see also a review in (Noy and Yonson, 2016). We also provide a comparison of our measure of socioeconomic resilience and our estimates of welfare risks with two other vulnerability or resilience indicators, namely ND-Gain and InfoRM. Our indicator 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; (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: Resilience and risk for all 90 countries

	GDP per capita USD PPP	**Population**	**Protection level** return period in years	**Asset exposure** % of GDP	**Asset vulnerability** % asset value	**Resilience** %	**Total risk** % of GDP
Albania	9,961	2,897,366	15.5	38.2	33.8	71.0	1.19
Argentina	8,087	41,446,246	64.4	27.3	32.3	52.9	0.21
Armenia	7,527	2,976,566	11.5	9.5	12.4	69.1	0.13
Australia	42,834	23,129,300	100.0	15.6	44.7	71.3	0.08
Austria	4,056	8,479,823	600.6	37.6	16.0	69.2	0.01
Azerbaijan	16,593	9,416,801	14.0	8.2	12.4	58.7	0.12
Bangladesh	2,853	56,594,962	50.0	76.7	38.0	64.2	0.76
Belarus	17,055	9,466,000	14.5	8.8	26.2	68.3	0.19
Belgium	0,609	11,182,817	213.0	51.0	14.7	76.5	0.04
Benin	1,733	10,323,474	6.4	10.5	60.3	41.7	2.04
Bolivia	5,934	10,671,200	6.7	10.3	25.4	48.2	0.73
Bosnia and Herzegovina	9,387	3,829,307	18.8	40.9	38.4	54.3	1.50
Botswana	15,247	2,021,144	16.7	10.8	55.8	55.4	0.50
Brazil	14,555	00,361,925	22.2	18.4	57.0	58.1	0.76
Bulgaria	5,695	7,265,115	28.3	12.4	39.3	67.2	0.21
Burkina Faso	1,630	16,934,839	1.9	2.0	60.0	70.8	0.82
Cambodia	2,944	15,135,169	5.3	24.5	24.5	48.1	2.44

Cameroon	2,739	22,253,959	6.7	7.8	17.0	30.5	0.61
Canada	1,899	35,154,279	84.1	11.3	13.9	69.6	0.02
Colombia	12,025	48,321,405	19.7	11.5	27.7	25.4	0.40
Congo, Dem. Rep.	783	67,513,677	2.0	11.4	51.1	60.1	4.85
Congo, Rep.	5,680	4,447,632	3.4	8.6	15.9	34.9	1.11
Costa Rica	3,431	4,872,166	17.0	3.8	17.9	45.4	0.07
Croatia	0,049	4,255,700	179.8	50.2	38.6	74.6	0.12
Czech Republic	8,124	10,514,272	86.8	29.3	39.0	76.0	0.14
Denmark	2,483	5,614,932	25.7	2.4	12.6	77.9	0.01
Dominican Republic	1,795	10,403,761	77.0	9.4	13.1	74.0	0.02
Ecuador	10,541	15,737,878	18.4	25.7	60.0	62.5	1.14
Egypt, Arab Rep.	10,733	82,056,378	31.4	38.5	47.2	49.7	0.94
El Salvador	7,515	6,340,454	6.8	6.2	32.7	63.6	0.40
Estonia	25,254	1,317,997	46.5	6.9	12.9	64.8	0.03
Finland	38,821	5,438,972	48.2	13.6	14.2	81.2	0.04
France	7,217	65,939,866	122.6	32.7	15.7	75.0	0.04
Gabon	18,646	1,671,711	16.9	25.5	21.5	29.3	0.97
Georgia	6,930	4,487,200	23.4	23.0	15.6	79.4	0.17
Germany	42,884	80,651,873	106.9	27.4	13.3	75.6	0.04
Greece	24,305	11,027,549	25.3	7.3	17.5	58.9	0.07
Guatemala	7,063	15,468,203	8.0	4.8	13.2	25.2	0.25
Honduras	4,445	8,097,688	7.2	11.0	24.6	65.6	0.60
Hungary	22,707	9,893,899	100.0	46.9	38.3	81.6	0.17
Ireland	44,647	4,597,558	200.0	12.5	12.8	71.1	0.01
Italy	33,924	60,233,948	62.6	23.4	15.0	64.8	0.07
Jamaica	8,607	2,714,734	0.5	0.1	26.7	49.5	0.06
Jordan	11,405	6,460,000	16.6	2.0	49.3	49.6	0.08
Kenya	2,705	44,353,691	2.1	3.3	51.6	38.9	1.56
Kyrgyz Republic	3,110	5,719,600	3.1	6.2	21.4	63.1	0.58
Lao PDR	4,667	6,769,727	6.8	65.9	14.1	56.8	2.34
Latvia	21,833	2,012,647	59.7	25.1	12.7	66.0	0.08
Liberia	850	4,294,077	6.1	11.7	60.0	59.7	2.08
Lithuania	24,470	2,957,689	49.8	25.8	15.3	72.8	0.11
Madagascar	1,369	22,924,851	2.2	11.6	32.2	58.8	2.51
Malawi	755	16,362,567	2.8	6.9	32.5	53.2	1.23
Malaysia	22,589	29,716,965	34.9	42.6	13.0	57.6	0.21
Mali	1,589	15,301,650	7.0	11.0	15.2	41.6	0.54
Mexico	16,291	122,332,399	39.4	16.5	39.4	59.3	0.23
Moldova	4,521	3,558,566	10.5	23.0	38.7	86.0	0.94
Mongolia	9,132	2,839,073	6.3	16.4	12.9	66.2	0.45
Nepal	2,173	27,797,457	2.3	17.0	34.2	81.5	2.94
Netherlands	45,021	16,804,432	4,489.6	133.2	12.8	75.3	0.00
Niger	887	17,831,270	2.5	9.3	15.5	64.5	0.85
Nigeria	5,423	173,615,345	7.0	3.7	60.2	33.6	0.72
Pakistan	4,454	182,142,594	7.2	17.4	49.7	59.5	1.74
Panama	18,793	3,864,170	14.3	3.0	60.0	47.5	0.23
Paraguay	7,833	6,802,295	20.1	7.0	32.1	46.9	0.19
Peru	11,396	30,375,603	93.1	26.1	30.1	73.7	0.11
Philippines	6,326	98,393,574	8.3	15.7	12.3	76.1	0.27
Poland	22,835	38,514,479	200.0	15.4	13.1	66.3	0.01
Romania	18,184	19,981,358	50.0	28.0	45.1	74.5	0.28
Rwanda	1,426	11,776,522	2.2	4.6	60.6	58.3	2.08

Senegal	2,170	14,133,280	5.2	10.2	61.8	77.0	1.39
Serbia	12,892	7,164,132	20.5	48.5	38.7	71.2	1.16
Sierra Leone	1,495	6,092,075	1.8	9.0	60.3	47.2	4.76
Slovak Republic	25,759	5,413,393	100.0	50.1	38.8	66.7	0.28
Slovenia	27,368	2,059,953	56.6	49.6	36.8	78.8	0.32
South Africa	12,454	53,157,490	100.0	4.3	55.7	46.0	0.05
Spain	31,683	46,617,825	98.2	25.1	11.0	73.8	0.04
Sri Lanka	9,426	20,483,000	6.4	15.6	60.7	65.3	1.84
Sweden	43,540	9,600,379	53.6	9.9	12.8	71.2	0.03
Syrian Arab Republic	4,959	22,845,550	9.0	17.0	40.3	61.4	1.06
Tanzania	2,365	49,253,126	2.0	4.0	32.6	55.0	1.09
Thailand	13,932	67,010,502	22.5	66.7	25.1	63.7	1.00
Turkey	18,567	74,932,641	18.2	6.7	32.4	55.2	0.19
Uganda	1,621	37,578,876	1.5	0.5	27.3	32.5	0.23
Ukraine	8,508	45,489,600	9.3	15.0	40.8	72.1	0.89
United Kingdom	36,931	64,106,779	225.7	14.1	12.8	68.3	0.01
United States	51,340	316,128,839	460.2	12.0	13.5	62.8	0.00
Uruguay	18,966	3,407,062	46.9	6.3	32.5	56.9	0.07
Vietnam	5,125	89,708,900	17.6	74.7	12.5	71.6	0.61
Yemen, Rep.	3,832	24,407,381	6.4	6.9	13.0	72.5	0.18
Zambia	3,800	14,538,640	6.5	3.8	32.8	30.8	0.45