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Measurement of Economic Welfare Risk and Resilience of the Philippine Regions

Abstract

Using an economic model to assess welfare risk and resilience to disasters, this paper systematically tackles the questions: 1) How much asset and welfare risks does each region in the Philippines face from riverine flood disasters? 2) How resilient is each region to riverine flood disasters? and 3) What are the available interventions per region to strengthen resilience to riverine flood disasters and what will be their measured benefit? We study the 18 regions of the Philippines to demonstrate the channels through which macroeconomic asset and output losses from disasters translate to consumption and welfare losses at the microeconomic level. Apart from the prioritization of regions based on resilience and welfare risk, we identify a menu of policy options ranked according to their level of effectiveness in increasing resilience and reducing welfare risk from riverine floods. While there are similarities in the ranking of policies among regions with comparable levels of resilience and welfare risk, the ranking of priorities varies for different regions. This suggests that there are region-specific conditions and drivers that need to be integrated into policies and development processes so that these conditions are effectively addressed. Overall, the results indicate that reduction of adverse disaster impacts, including welfare losses, and reduction of poverty are generally complementary.

JEL-Codes: Q540.

Keywords: disasters, floods, risk, resilience, floods, Philippines.

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1 Introduction

Among the consequences of damages to assets due to disasters are losses in output and income that, in turn, result in consumption and welfare[1] losses (Hallegatte et al., 2016a, 2016c). These losses of welfare are often not reported, nor even quantified. The scant empirical literature on welfare impacts is often cross-national or focused on one limited area within a country (e.g. a particular city or province or district, etc). We aim to fill these gaps by conducting an intra-national assessment of the welfare impacts of and resilience to riverine floods.

We study the Philippine regions, all of which are prone to riverine floods caused by heavy rainfall and by the presence of many river systems across the country[2]. The country is one of the most at-risk to different hazards worldwide (UNU-EHS, 2014). The centralized system of allocation of fiscal resources; the integrated nature of development planning, investment programming, and budgeting; and, the decentralized system of governance make the country a suitable test-case to demonstrate the practical usefulness of the economic model we use and of our assessment outputs to inform policy decisions.

In this study, we answer the following broad questions: 1) How much asset and welfare risk does each region face from riverine flood disasters? 2) How resilient is each region to riverine flood disasters? 3) What are the available interventions per region to strengthen resilience to riverine flood disasters and what will be their benefit?

We use the economic model by Hallegatte (2014) that extends the usual hazard-exposure-vulnerability disaster risk model into an economic welfare disaster risk model (henceforth, the Model). The Model accounts for the fact that assets damaged during a disaster ultimately cause adverse impacts on the welfare of affected individuals (Hallegatte et al., 2016a). The Model quantifies welfare risk[3], which is the annual welfare losses expressed as the equivalent consumption losses, by adding socioeconomic resilience as a fourth component of the hazard-exposure-vulnerability disaster risk model (Hallegatte et al., 2017). Socioeconomic resilience, or simply resilience under the Model, is defined as the economy's ability to minimize people's welfare losses consequent to asset losses brought by a disaster (Hallegatte, 2014). This definition is considered as "one part of the ability to *resist, absorb, accommodate and recover in a timely and efficient manner*

[1] "Welfare" in Economics approximates "well-being" in daily parlance. It is defined in the Oxford Dictionary of Economics as the "state of well-being of an individual or a society. The level of welfare measures the degree of contentment of an individual or a society" (Black et al., 2009).
[2] The Philippines has a total of 18 major river basins, with a drainage area of more than 1,000 square kilometres, and 421 principal river basins (PAGASA-DOST, 2012).
[3] Risk to welfare, expected welfare losses, and annual welfare losses are alternative terms referring to welfare risk.

to asset losses (the qualitative definition of resilience from the United Nations)" (Hallegatte, Bangalore, & Vogt-Schilb, 2016b).

The Model had been applied empirically to a city and cross-national assessments. The Model was first empirically applied to Mumbai City and to 90 countries for a single hazard assessment (i.e. flood), and to 117 countries for a multi-hazard assessment (Hallegatte, 2014; Hallegatte et al., 2016a, 2016b, 2016c). For our application of the Model to the Philippine regions, we adopt with a number of modifications the estimation algorithm and assumptions used in the single hazard application for 90 countries in Hallegatte et al. (2016a). As needed, we use alternative proxy indicators and make appropriate adjustments to the assumptions to better reflect the specific circumstances of the Philippine regions[4].

A cross-national assessment has limited value for making actual policy decisions, though it provides important general insights on the drivers of welfare risk and resilience. First, because there is no single global policy-making authority that is in charge of identifying priority countries and priority policies within each country, and of funding these priorities for each country.[5] Second, because the costs of policy options are likely to differ across countries, thereby making the cross-national comparison of benefits generated from the assessment less meaningful. Meanwhile, an assessment specific to a subnational area (such as a particular city) likewise has a limited usefulness in typical contexts where resources are largely centrally determined and allocated. Results of such assessment cannot provide insights on the level of priority that must be given to this specific area relative to the other places.

Thus, our subnational assessment, with an intra-national spatial disaggregation (i.e. regions) and analysis has greater practical significance for policy-making. One, because there is a single policy-making authority across regions. Second, because costs are likely to be similar across these regions, the prioritization of policies based on benefits we compute are more useful than those in cross-country analysis. Through this assessment, we take advantage of the Model's systematic assessment of welfare risk and resilience to disasters, and further demonstrate how the Model can be adjusted to be of greater usefulness to policy-making, and at the same time add value to the development process of our study area.

In sum, our main contribution to the model is in terms of demonstrating the Model's flexibility (i.e how it can be modified to a given context), and demonstrating at what level of analysis it is most

[4] The specific adjustments we make are indicated in appropriate parts in Section 4. Model, Dataset, and Descriptive Statistics.
[5] At best, there are the multilateral and aid organizations which may have a global reach but with different development foci and agendas.

suitable and practicable. Our final outputs are the prioritization of regions based on estimated resilience and welfare risk, and policy cards for each of the 18 regions of the country. The former can be useful for national development planning given the imperative to allocate resources efficiently at various subnational levels amidst the limits of the country's fiscal resources to fund its many development needs. The latter has at least two purposes: one, as a tool to track regional level progress; and, two as a menu of policy options prioritized according to their effectiveness in reducing asset and welfare risk, and increasing resilience per region. The prioritized policy options can be used as guide for investment programming and budgeting.

This paper is organized into six sections. Section 2 provides a quick review of literature on the factors affecting resilience, while Section 3 provides a brief background on Philippine development and riverine flood disasters. Section 4 presents further details on the Model, as well as the data and assumptions we use. Section 5 discusses the results, while Section 6, the general implications and caveats.

2 Literature Review

There is now a significant economic literature that aims to measure the follow-on economic impacts of disasters typically in either the short-run (months to several years) or long-run (at least 3 to 5 years). These studies also attempt to understand the factors that influence these impacts, thereby also providing insights on the determinants of economic resilience to disaster.

In a cross-country study, Felbermayr and Gröschl (2014) find substantial reduction in GDP per capita in the aftermath of disasters, with the low to middle income countries incurring greater declines. Further, greater financial and trade openness, as well as better institutions, facilitate the reconstruction thereby preventing large declines in GDP per capita. These are largely consistent with earlier empirical work. Noy (2009) finds that countries with higher income per capita, greater trade openness, and higher literacy rates, higher levels of public spending, and better institutions are able to withstand the initial impacts of disasters, and cope better. He attributes this to the capacity for resource mobilization to implement the necessary reconstruction. Likewise, Loayza, Olaberría, Rigolini, and Christiaensen (2012) find that greater trade openness is positively associated with growth.

Unlike Felbermayr and Gröschl (2014), Noy (2009) findS that while an increase in asset damage results in reduced output growth among developing countries, the opposite is seen for developed countries. A similar finding is seen at the subnational level. An assessment of economic impacts among the provinces of Vietnam reveals that areas with higher levels of development, and those that have better access to funds for reconstruction from the central government experience a consequent short-run growth spurt in the disaster aftermath (Noy & Vu, 2010). These are consistent with the earlier cross-country findings of Cuaresma et al. (2008) that countries with high level of development benefit from capital upgrading for assets damaged during a disaster.

Hochrainer (2009) uses a counterfactual to the observed post-disaster output level in the medium-term and in the long-term (five years). Similarly, he finds evidence of negative (but small) consequences of the disaster on the capital stock and therefore on macroeconomic output. Inflows of remittances and aid reduce the adverse macroeconomic consequences. He finds that a disaster with damage to the capital stock of above a value of 1% of GDP would overwhelm the internal capacity of the country to self -finance post-disaster reconstruction needs, hence the importance of aid.

In an attempt to determine welfare changes due to the occurrences of disasters, Mechler (2009) measures the corresponding changes in consumption, instead of the usual changes in GDP[6]. Results for a cross-country analysis reveal that asset losses do not cause significant changes in consumption. However, by narrowing the sample to low-income countries only, asset losses do adversely alter consumption. Further, results show that inflows of regular and post disaster aid likewise do not result in significant changes in consumption, except among low-income countries.

Meanwhile, von Peter, von Dahlen, and Saxena (2012) provide robust evidence on the influence of insurance in post disaster dynamics of countries. On top of the immediate damage to assets, there are likewise output losses incurred for several years following the disaster. By disaggregating the total losses into uninsured losses and insured losses, they show that these macroeconomic costs are largely due to uninsured losses. Interestingly, insured losses either do not have adverse impacts on economic activities, or result in positive impacts.[7] Small and low-income countries experience quicker recovery when losses are insured, but incur more negative economic impacts otherwise.

At the firm level, Poontirakul, Brown, Noy, Seville, and Vargo (2016) study the role of commercial insurance among the firms affected by the 2011 earthquake in Christchurch, New Zealand. While

[6] In assessing the welfare impact of disasters, indicators of production and outputs, such as GDP and its variants, are commonly used as a proxy for welfare, though consumption is arguably a better proxy (Mechler, 2009). In general, production only indicates how much is made available, while consumption indicates how much is actually used (consumed). It therefore better captures the economic concepts of utility and standard of living. From a Utilitarian perspective, consumption is what matters most, and not output and production (Hallegatte & Przyluski, 2010).

[7] The authors find that for geologic hazards (such as volcanic eruptions and earthquakes), insurance offsets the adverse impacts, while among hydrometeorological hazards (such as floods and storms), insurance

there is no clear role of insurance on firm recovery in the short-term,[8] there are however evident positive effects in the medium-term. This is particularly true among firms that received their insurance claim payments promptly.

It is noted however that while insurance facilitates recovery, access to market insurance is limited mainly to high-income countries, and to the better off sectors of society. Often the poor only have access, if at all, to publicly funded social insurance mechanisms that often offer limited or inadequate coverage.

External sources of funds and assistance, such as aid, remittances, social protection, and insurance, are likewise critical for household-level post-disaster recovery. Arouri et al. (2015) undertook a household level study in Vietnam to determine the effects of disasters on household welfare, and the characteristics of households and communities that made them resilient to the adverse disaster impacts. Internal remittances are found to be an important contributor of household resilience to floods, storms and droughts. Likewise, access to finance—such as microfinancing, international remittances and social allowances - positively affect resilience. Households in communes with either a more equal distribution of expenditure or a higher level of average per capita expenditure are also better able to respond to the shock (Arouri et al., 2015).

These findings on the importance of access to finance are further supported by a study by Hudner and Kurtz (2015) among families affected by Typhoon Haiyan in the Philippines. Savings and loans, despite through informal schemes, make families feel that they are better able to cope or be resilient. Further, they find that social capital is positively associated with resilience. This is widely supported by the finding of Aldrich (2015) in his study on strength of networks and communities in East Asia in the aftermath of disasters. On the other hand, Ravago and Mapa (2014) find that households affected by Typhoon Haiyan that undertook pre-cautionary measures, including asset accumulation, savings and informal insurance, have higher probability of recovery. Post-disaster coping actions such as dissaving and borrowing likewise facilitate recovery.

Among households affected by landslides in Uganda, Mertens et al. (2016) find that those with fewer assets (measured in terms of land) experience more severe impacts on income relative to those with more assets. Results also suggest that households sought external and/or alternative sources of income to offset income losses due to the landslides. Households that experienced a

[8] The authors note that this could either be due to the limits of their dataset or the effectiveness of insurance provider in the immediate aftermath.

landslide in the previous year were more likely to get a job in other farms or engage in self-employment activities.

Overall, the results of the above empirical studies indicate that a high level of socio-economic development, whether at the national, subnational, or at the household level, reduces adverse economic impacts and improves resilience. While there is no clear agreement on the direction of impact of asset damage on macroeconomic output using a sample of low and high-income countries, there is apparent evidence that developing countries incur adverse impacts. Policies and actions that are most effective in minimizing follow-on economic impacts and spillover effects are mainly about adequate access to funds to speed up the reconstruction, rehabilitation, and subsequent economic recovery.

We operationalize the insights outlined above into our assessment, while at the same time addressing a gap in the empirical literature. No assessment simultaneously covers both macroeconomic and microeconomic aspects of this challenge[9]. The inclusion of both macroeconomic and microeconomic considerations in assessing resilience is one of the key advantages of the Model we use. Importantly, the Model applies economic theory and economic insights from related theoretical and empirical literature on the channels through which disaster asset losses at the macroeconomic level lead to welfare losses at the microeconomic level. Further, the Model takes into account important considerations that are relevant in the context of the Philippines, such as socioeconomic heterogeneity, in order to measure the disparity in welfare risk, with a specific focus on losses for the poor.

3 Philippine Development and Riverine Flood Disasters

The Philippines is an archipelago comprising of 18 regions that are grouped into three major island groups: Luzon, Visayas and Mindanao (Figure 1). As of 2015, the country has a projected population of over 101 million (PSA, 2016a). With a GNI per capita of USD3,550 in 2015, the Philippines is classified by the World Bank as a lower middle-income country (WB, 2016).

Several aspects of the country's physical and socio-economic characteristics influence its exposure, vulnerability, and resilience to disasters. Natural hazards occur frequently given the country's

[9] The focus of studies employing econometric methods on either the macro level or micro level of inquiry is likely due to the complexity of using a single econometric model to capture both levels. Adding to this is the difficulty of putting together useful macro and micro level datasets. Other useful methods that allow for macro-micro analysis include computable general equilibrium (as proposed in Rose (2004a) and Rose and Krausmann (2013)), partial equilibrium analysis (as in Hallegatte (2014)), and other mathematical algorithms.

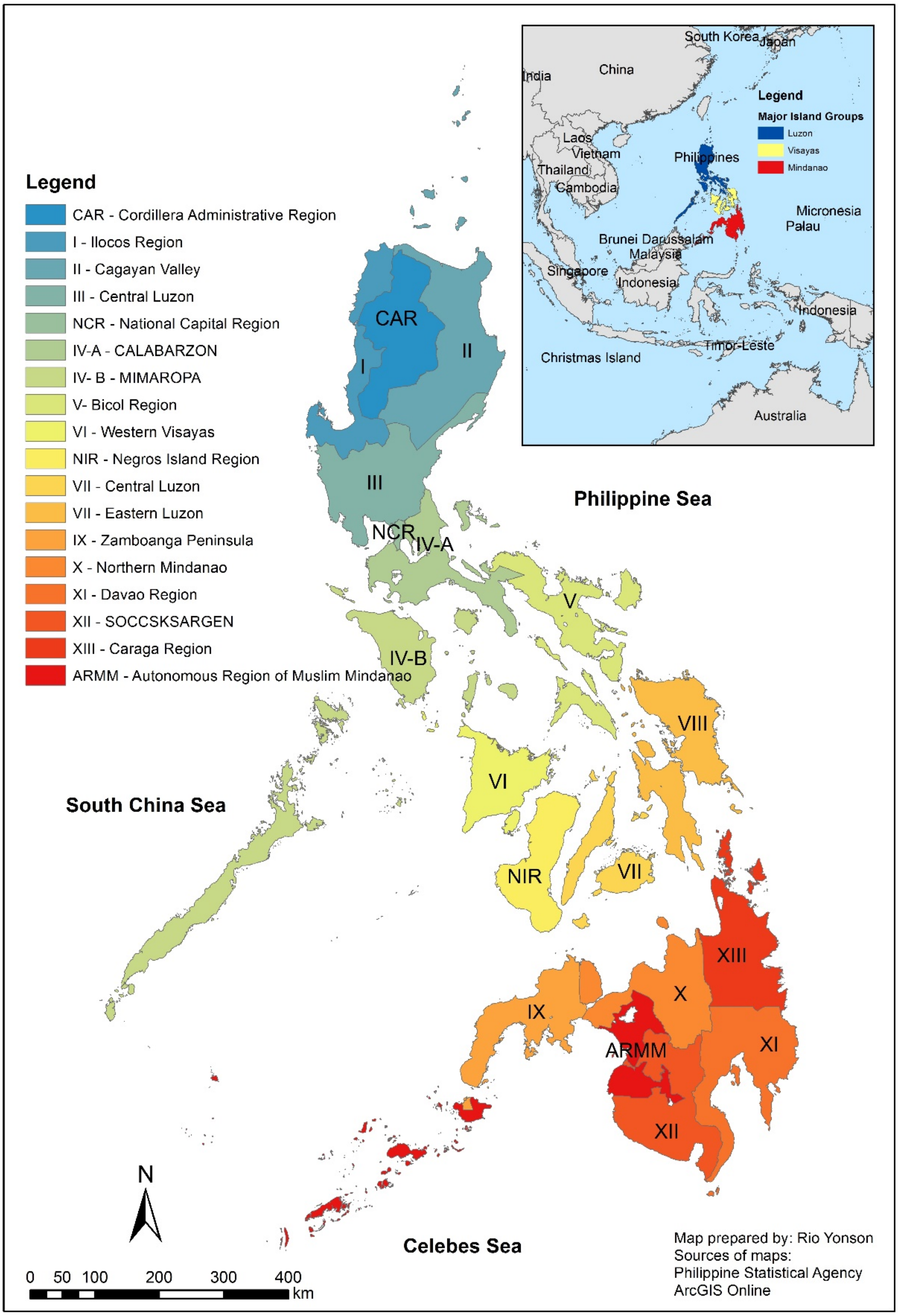
geographic, geologic and meteorological setting. It is located along the Pacific Ring of Fire and along the Pacific typhoon belt, thus making it prone to various geologic and hydrometeorologic hazards.

A number of highly destructive riverine floods in the country occurred in recent years:

- In September 2009, the Marikina River[10], rose 23 meters as Tropical Storm[11] (TS) Ketsana poured a rainfall volume that surpassed the country's forty-year record high (Abon, David, & Pellejera, 2011).[12]
- Also in September 2009, Typhoon Parma likewise brought massive riverine floods in the national capital and in its neighbouring provinces (GOP, 2009). The combined damage and loss brought by these two tropical cyclones (Ketsana and Parma) reached USD4.38 billion, equivalent to 2.7% of the country's GDP in 2009 (GOP, 2009).
- In December 2011, Tropical Storm Washi that poured a month's worth of rain in just 24 hours in the Northern Mindanao region, brought substantial swelling in four river basins traversing four provinces (NEDA, 2012; TCAGP, 2014). The majority of the 1,258 deaths and USD48 million in damage to properties were due to the resulting floods (NDRRMC, 2012b).

[10] Marikina River is the largest river system in the country's National Capital Region.
[11] In the Philippines, a typhoon is a tropical cyclone with a maximum wind speed of above 118 kilometres per hour (kph), while a tropical storm has a maximum wind speed of 64 kph to 118 kph. A third classification is tropical depression, which has a maximum wind speed of 63 kph (PAGASA, undated).
[12] In 2012, the same river swelled 20.6 meters up due to torrential southwest monsoon rains, again resulting in much devastation (Heistermann et al., 2013; Marueñas, 2015).

Figure 1. The 18 Regions of the Philippines



Typhoon Bopha in 2012, and Typhoon Haiyan in 2013 passed the PAR with unprecedented strength in the respective exposed areas in the central and southern part of the Philippines. Accompanied with other hazards such as riverine floods, landslides, and storm surges, these tropical cyclones became the most lethal and destructive in the country in these years. Typhoon Haiyan left a staggering trail of 6,092 deaths, while Typhoon Bopha claimed 1,258 lives (NDRRMC, 2014). Moreover, they were the most costly disaster events in the country in the said years (NDRRMC, 2014). Yonson et al. (2016) show that death toll from tropical cyclones in the Philippines is mostly because of water and not wind speed.

A critical and persisting development concern of the country is poverty, which is also deemed an important underlying factor for hazard exposure, vulnerability, and resilience. As of 2015, poverty incidence among population and among families was 26.3% and 22.3%, respectively. Without access to land, poor people crowd and build makeshift houses in informal settlements that are hazard prone, including along the rivers and coastal areas (Gaillard, 2008; Gaillard et al., 2007; Ginnetti et al., 2013; WB-EASPR, 2003).

Apart from being a driver of disasters, poverty in the Philippines is likewise a consequence of disasters, whether natural or human-induced (ADB, 2007). Regions V and VIII, the poorest regions in Luzon and Visayas, respectively, lie along the eastern coastline where tropical cyclones first enter the Philippines (NEDA, 2014). These regions have experienced some of the worst disasters in Philippine history.

The rapid population growth and unplanned urbanization of the country have also been taking a toll in terms of increasing risk to disasters.[13] High levels of urban poverty resulted in greater hazard exposure and vulnerability. Recognizing the gravity of the impact of disasters on the poor, the country expanded its conditional cash transfer program to offer post-disaster assistance to affected poor families. Specifically in 2012, the Modified Conditional Cash Transfer was implemented to provide cash grants for children's education and the health needs of families in difficult situations including those affected by disasters (DSWD, 2013).

The huge historical annual losses of lives and properties, along with the projected incremental damage due to climate change, depict the glaring reality that the Philippines has yet to match the increasing intensity of hazards and gravity of disaster impacts with heightened effectiveness in prevention and mitigation measures. For countries where there is certainty of hazard recurrence, it is imperative to supplement actions to reduce exposure and vulnerability with interventions that increase peoples' capacity to cope (Hallegatte et al., 2017).

[13] The Philippine population grew at an average of 2.69% during the period 1950-2010 higher than the averages for South East Asia, the whole of Asia and the World (UN, 2014). Urban population grew much faster, driven mainly by migration of people from rural areas. During the period 1950 – 1990, urban population grew at an annual average of 4.47%, also higher than the averages for South East Asia, the whole of Asia and the World (UN, 2014). Thereafter, urban annual population growth rate slowed down, ranging from 1.12 to 2.21% from 1990 to 2010.

It is towards this end of identifying context-specific interventions to strengthen people's ability to avoid welfare losses and increase resilience that we conduct this study. Our final research outputs can be easily integrated into the existing efforts of mainstreaming disaster risk reduction and management, and climate change adaptation in the development process.

4 Model, Dataset, and Descriptive Statistics

4.1 Economic Welfare Disaster Risk Model

This section is largely based on Hallegatte (2014), Hallegatte et al. (2016a), Hallegatte et al. (2016b), and (Hallegatte et al., 2017). Modifications made for the Philippine application in terms of estimation algorithm and assumptions are indicated either in the footnote or integrated into the main text[14].

The Model operationalizes the quantification of welfare risk[15] by adding socioeconomic resilience as a fourth component into the typical hazard-exposure-vulnerability disaster risk model, as follows: $$Welfare\ Risk = \frac{(Hazard) x\ (Exposure) x\ (\ Vulnerability)}{(Socioeconomic\ Resilience)} = \frac{Expected\ Asset\ Losses}{Socioeconomic\ Resilience} \quad (1)$$

where the definitions of hazard, exposure, and vulnerability of assets are aligned with the definitions of UNISDR (2009) as follows: *Hazard* refers to a natural phenomenon that may cause damage to assets, and quantitatively expressed in terms of the probability for the hazard to occur and its intensity; *Exposure* refers to assets located in hazard-prone areas; and, *Vulnerability* refers to the characteristics of assets that make them be adversely affected by the hazard, and is quantitatively expressed as the proportion of asset that is lost as a result of the disaster (Hallegatte et al., 2017). Socioeconomic resilience is quantitatively defined as:

$$Socioeconomic\ Resilience = \frac{Asset\ Losses}{Welfare\ Losses} \quad (2)$$

4.1.1 Macroeconomic Assessment

The analysis in the Model takes off from the classical production function where capital and labour are the factors of production, Y = f (K, L). When a disaster occurs, the economy incurs damage to

[14] Modifications in the equation and/or algorithm are typically explained in the footnote to avoid disruption of the flow of the discussion of the Philippine application. Assumptions, either modified or adopted from the Hallegatte et al (2016a), are indicated in the main text
[15] Henceforth, we use welfare risk or risk to welfare to refer to economic welfare disaster risk.

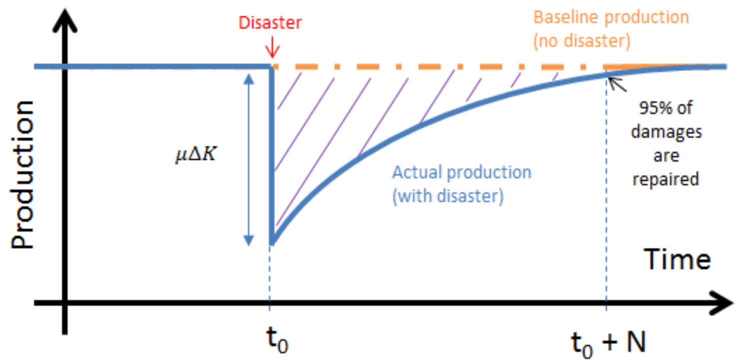
capital or asset losses, ΔK. This consequently leads to a decline in production capacity, and, therefore, the economy incurs output losses, ΔY.[16]

Figure 2 is a simplified illustration of losses in output consequent to the damage on assets brought by disasters, and the return to the baseline output over time after the completion of reconstruction. In this illustration, the shock due to the disaster occurs at t_0. The immediate result is the reduction in the stock of capital. Due to the disruption in production, output drastically falls:

$$\Delta Y(t_0) = \mu \Delta K \tag{3}$$

where ΔY is output losses, ΔK is the damage to capital or asset losses, and μ is the average productivity of capital. It is noted that the Model uses average productivity of capital instead of the marginal productivity of capital that is typically used in the assessment of output losses.[17]

Figure 2. Reconstruction Dynamics and Total Output Losses



Source: Hallegatte et al. (2016b)

By how much output continues to decline in the aftermath depends mainly on the reconstruction dynamics. With the assumption that output losses are exponentially reduced to zero and 95% of the losses is repaired exponentially in N years, output losses are likewise reduced exponentially. Thus, post-disaster output losses at year t is:

[16] We note that asset losses and output losses are alternative typologies of economic costs that are, to an extent, distinct from the usual *direct damage* and *indirect loss* typology used by the ECLAC. Specifically, asset losses here refer to reduction in the value of the *stock* of assets or capital, while output losses refer to the reduction in the income *flow* (Hallegatte, 2014). Thus, this typology of economic costs is consistent with the damages to stocks and flows of Rose (2004a) rather than with the ECLAC direct damage and indirect loss typology.

[17] This is because the use of marginal productivity of capital underestimates the output losses (Hallegatte et al., 2016c). This can be due to any or a combination of the following reasons, among others: damaged assets may generate positive externalities, thus making the damaged assets to be valued more by the society than by owner of the assets; non-marginal shocks affects the structure of the economy and the relative prices of goods; presence of further effects from the damaged assets that prevent the other unaffected assets to produce at pre-disaster levels (Hallegatte et al., 2016c).

$$\Delta Y(t) = \mu \Delta K e^{-\frac{t-t_0}{N/3}} \qquad (4)^{18}$$

where $\Delta Y\ (t)$ is the output losses at a post-disaster time t; N is the time it takes to repair 95% of the damaged assets; and, ΔK, and μ are as defined earlier. At year t_0 + N, Equation 4 is equal to $\Delta Y(t_0 + N) = \mu \Delta K e^{-3}$, or $\Delta Y(t_0 + N) = \mu \Delta K\ (0.05)$, which is equivalent to $\Delta Y(t_0 + N) = 0.05\ \Delta Y(t_0)$. That is, after N years of reconstruction from the year of the disaster, the output level has returned to 95% of its pre-disaster level.

Overall, the net present value (NPV) of output losses, $\widetilde{\Delta Y}$, is as follows:

$$\widetilde{\Delta Y} = \int_{t_0}^{+\infty} \mu \Delta K e^{-\frac{t-t_0}{N/3}} e^{-\rho(t-t_0)} dt = \mu \Delta K \frac{N}{\rho N + 3} \qquad (5)^{19}$$

where ρ is the discount rate; and, ΔK, μ and N are as defined earlier.

The losses in macroeconomic outputs result in losses in aggregate consumption equal to the NPV of cost to reconstruct the damaged capital, and the NPV of output losses, as follows:

$$\widetilde{\Delta C} = \int_{t_0}^{+\infty} \left((\mu \Delta K e^{-\frac{t-t_0}{N/3}} + \Delta K e^{-\frac{t-t_0}{N/3}} \frac{3}{N} \right) e^{-\rho t} dt = \Delta K \overbrace{\frac{\mu + 3/N}{\rho + 3/N}}^{\Gamma} \qquad (6)^{20}$$

where $\widetilde{\Delta C}$ is the NPV of consumption losses integrated over N years; and, ΔK, μ, ρ, and N are as defined earlier. Γ is an amplifying factor that indicates that NPV of the flow of consumption losses across N years to reconstruct 95% of the asset damage are greater than damage to capital multiplied by the average productivity of capital.

The Model assesses welfare impacts by translating the macroeconomic assessment indicated in Equations 1 to 6 into a microeconomic assessment. It takes into account socioeconomic heterogeneity to capture the disparity in welfare losses among the poor and the non-poor. This entails decomposing exposure and vulnerability into those of poor and non-poor families, i.e., into

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[18] Equation 4 is a modified version of Equation 5 in Hallegatte et al. (2016c), $\Delta Y(t) = (1+\alpha)\mu \Delta K e^{-\frac{t-t_0}{N/3}}$, where (1+α) represents "ripple effects". These effects represent the situation where the damaged assets made some other assets (that were not affected by the disaster) less productive in the aftermath of the disaster, such as in the case of closure of an entire road segment as a result of a damaged part of that segment (Hallegatte et al., 2016c).

[19] Equation 5 is a modified version of Equation 6 in Hallegatte et al. (2016c), $\widetilde{\Delta Y} = \int_{t_0}^{+\infty} \mu \Delta K e^{-\frac{t-t_0}{N/3}} e^{-\rho(t-t_0)} dt = (1+\alpha)\, \mu \Delta K \frac{N}{\rho N+3}$ which includes ripple effects.

[20] Equation 6 is a modified version of Equation 7 in Hallegatte et al. (2016c), $\widetilde{\Delta C} = \int_{t_0}^{+\infty} \left((\mu \Delta K e^{-\frac{t-t_0}{N/3}} + \Delta K e^{-\frac{t-t_0}{N/3}} \frac{3}{N} \right) e^{-\rho t} dt = (1 + \alpha) \Delta K \overbrace{\frac{\mu + 3/N}{\rho + 3/N}}^{\Gamma}$ which includes ripple effects.

exposure and vulnerability for the poor and for the non-poor families. Further, families are categorized into the "directly affected" and "not directly affected" (Hallegatte et al., 2016c). The former are those who experienced the disaster first hand, while the latter are those who have been affected through risk sharing mechanism, which in this analysis is proxied by the private transfers and the government social protection program (Hallegatte et al., 2016c). Table 1 below shows how the exposure for each of the four categories of families are computed.

Table 1. Exposure by Category of Families

	Directly affected	Not directly affected
Poor	$n_p^a = p_h f_p^a\, n$	$n_p^n = p_h(1 - f_p^a)n$
Non-poor	$n_r^a = (1 - p_h)f_r^a\, n$	$n_r^n = (1 - p_h)(1 - f_r^a)n$

Source: Table 1 in Hallegatte et al. (2016c)

where p_h is poverty incidence; *n* is the total number of families; n^a and n^n is the number of families directly affected and not directly affected, respectively, with the subscripts *p* and *r* indicating whether poor or non-poor; and, f_p^a is a fraction of poor families affected by disaster to the number of poor families in the province[21], and f_r^a is for the non-poor.

By how much consumption declines in the event of a disaster depends on the families' pre-disaster and post-disaster sources of income, including access to protective mechanisms as these affect the ability of affected families to cope with the disaster impacts. Income comes from labour using assets that are located where the family resides; and, from transfers or risk sharing mechanisms that are diversified at the national level. Considering these, the consumption of poor and non-poor families is computed as follows:

$$c_i = \overbrace{(1 - \lambda_i)c_i}^{c_i^l} + \overbrace{\lambda_i c_i}^{c_i^d} \quad (7)$$

where *i* indicates whether the family is poor ($i = p$) or non-poor ($i = r$); c_i^l is the consumption using income from labour, c_i^d is the consumption using the transfers received; λ_i is the share of family income from transfers or risk sharing mechanisms, $1 - \lambda_i$ is the share on family income from assets used.

The Model assumes that over the short-term, consumption is linearly determined by the stock of assets as follows:

[21] f_p^a is derived from poverty exposure differential, $PE = \frac{f_p^a}{f^a} - 1$, where PE is set at 20%. Poverty exposure differential (originally poverty exposure bias (Hallegatte et al., 2016b)) is measure the exposure of the poor relative to the overall exposure of families (Hallegatte et al., 2016b).

$$c_i = \mu\left(\overbrace{(1-\lambda_i)k_i}^{k_i^l} + \overbrace{\lambda_i k_i}^{k_i^d}\right) \quad (8)$$

where k_i is the capital used by the poor (k_p) or the non-poor (k_r), whether the capital is located local (k_i^l) or diversified at the national level (k_i^d); and μ is the average productivity of capital. Equation 8 implies that consumption losses in the aftermath of a disaster is proportional to asset losses. It is noted that the Model makes the simplifying assumption that when a family is affected by a disaster, all of the capital used for generating income are likewise affected.

The extent of damage to capital used depends on the physical vulnerability of the assets used by the poor (V_p) and by the non-poor (V_r). It is assumed that assets used by the poor have greater vulnerability than the assets used by the non-poor. The vulnerability of capital diversified at the national level, whether among the poor or non-poor, are assumed equal to the vulnerability of capital of the non-poor. Table 2 summarizes how the capital or asset losses for each of the four categories of families are computed, where all variables are as defined earlier.

Table 2. Asset Losses by Category of Families

	Directly affected	**Not directly affected**
Poor	$\Delta k_p^a = V_p(1-\lambda_p)k_p + f_p^a V_r \lambda_p k_p$	$\Delta k_p^n = f_p^a V_r \lambda_p k_p$
Non-poor	$\Delta k_r^a = V_r(1-\lambda_r)k_r + f_r^a V_r \lambda_r k_r$	$\Delta k_r^n = f_r^a V_r \lambda_r k_r$

Source: Table 2 in Hallegatte et al. (2016c)

The macroeconomic consumption losses shown in Equation 6 is translated into the microeconomic level as follows:

$$\widetilde{\Delta c}_i = \Gamma \Delta k_i \quad (9)$$

where Γ is as defined earlier in Equation 6. Substituting the formula for the computation of asset losses for each category of family shown in Table 2 into Equation 9 results in the formula for computing the NPV of consumption losses by category of families shown in Table 3 below.

Table 3. NPV of Consumption Losses by Category of Families (without scale-up of protective mechanisms)

	Directly affected	Not directly affected
Poor	$\widetilde{\Delta c_p^a} = \Gamma V_p\left(1-\lambda_p\right)k_p + \Gamma f_p^a V_r \lambda_p k_p$	$\widetilde{\Delta c_p^n} = \Gamma f_p^a V_r \lambda_p k_p$
Non-poor	$\widetilde{\Delta c_r^a} = \Gamma V_r(1-\lambda_r)k_r + \Gamma f_r^a V_r \lambda_r k_r$	$\widetilde{\Delta c_r^n} = \Gamma f_r^a V_r \lambda_r k_r$

Source: Table 3 in Hallegatte et al. (2016c)

In the aftermath of a disaster, the adequacy of protective mechanisms such as transfers, social protection, remittances or insurance largely influence the capacity of affected families to smooth their consumption (Hallegatte et al., 2016b), particularly among the poor who are faced with binding financial constraints. Thus, with the scaled-up provision of these protective mechanisms in response to the disaster, the NPV of consumption losses for each category of families are as shown in Table 4.

Table 4. NPV of Consumption Losses with Scaled-Up Social Protection by Category of Families

	Directly affected	Not directly affected
Poor	$\widetilde{\Delta c_p^a} = \Gamma V_p\left(1-\overline{\lambda_p}\right)k_p + \Gamma f_p^a V_r \overline{\lambda_p} k_p$	$\widetilde{\Delta c_p^n} = \Gamma f_p^a V_r \overline{\lambda_p} k_p$
Non-poor	$\widetilde{\Delta c_r^a} = \Gamma V_r\left(1-\overline{\lambda_r}\right)k_r + \Gamma f_r^a V_r \overline{\lambda_r} k_r$	$\widetilde{\Delta c_r^n} = \Gamma f_r^a V_r \overline{\lambda_r} k_r$

The set of formulas in Table 4 differs from that in Table 3 by $\overline{\lambda_p}$ and $\overline{\lambda_r}$, which captures the scaled-up provision of protective mechanisms. Specifically, $\overline{\lambda_p} = 1 - (1-\lambda_p)(1-\sigma_p)$ and $\overline{\lambda_r} = 1 - (1-\lambda_r)(1-\sigma_r)$, where σ_p and σ_r is the proportion of losses of the directly affected poor and non-poor families, respectively, that is transferred to the rest of the families elsewhere in the country.

The consumption losses of the poor and non-poor are translated into welfare losses of the poor and non-poor through the application of distributional weights. Given the higher marginal utility of income and consumption among the poor, it is assumed that consumption losses among the poor carry more weight than the losses in consumption among the non-poor. Welfare in the region is computed as follows:

$$W = n_p w\left(\widetilde{c_p}\right) + n_r w(\widetilde{c_r}) \qquad (10)$$

where $w(\tilde{c})$ is the constant relative risk aversion welfare function[22] that links the NPV of consumption with the welfare of the affected family; $\left(\widetilde{c_p}\right)$ and $\left(\widetilde{c_p}\right)$ is the NPV of consumption of the poor and non-poor families, respectively; and, n_p and n_r are as defined earlier in Table 1.

[22] $w(\tilde{c}) = \frac{\tilde{c}^{1-\eta}-1}{1-\eta}$ where η is the constant that measures risk aversion. We adopt the assumption that $\eta = 1.5$, thereby putting greater weight on the consumption losses of the poor (Hallegatte et al., 2016b).

Welfare loss from consumption losses is then computed as the change in welfare prior to and after the disaster for all four categories of families:

$$\Delta W = \quad n_p^a \left(w(\widetilde{c_p}) - w(\widetilde{c_p} - \widetilde{\Delta c_p^a}) \right) + n_p^n \left(w(\widetilde{c_p}) - w(\widetilde{c_p} - \widetilde{\Delta c_p^n}) \right)$$

$$+ n_r^a \left(w(\widetilde{c_r}) - w(\widetilde{c_r} - \widetilde{\Delta c_r^a}) \right) + n_r^n \left(w(\widetilde{c_r}) - w(\widetilde{c_r} - \widetilde{\Delta c_r^n}) \right) \qquad (11)$$

where $w(\widetilde{c_p})$ and $w(\widetilde{c_p} - \widetilde{\Delta c_p^a})$ is the pre- and post-disaster welfare, respectively, of the poor; $w(\widetilde{c_r})$ and $w(\widetilde{c_r} - \widetilde{\Delta c_r^a})$ is the pre- and post-disaster welfare, respectively, of the non-poor; and, n_p and n_r are as defined earlier.

We note that the global model, either in Hallegatte et al. (2016a) or in Hallegatte et al. (2016b), also considers welfare losses from poverty traps. The rationale is that not all poor people have the capacity to smooth consumption over time through insurance (either market insurance or self-insurance through savings) and access to credit (Hallegatte et al., 2016a). While this is valid particularly in the context of the Philippines, we drop this from the estimation given the absence of data on either savings or insurance.

Once welfare loss is determined, socioeconomic resilience is computed using Equation 2, and welfare risk is computed simply as the product of hazard (probability of occurrence in a year) and welfare loss, as follows:

$$Welfare\ Risk = Hazard\ x\ Welfare\ Loss \qquad (12)$$[23]

4.2 Data and Assumptions

Our choice of indicators is guided by those used in the global model, which are among the indicators found to be robustly related to disaster risk and resilience in the empirical literature. As needed, we use alternative proxy indicators and make appropriate adjustments to the assumptions to better reflect the specific circumstances of the Philippine regions. For data not readily available from Philippine sources, we utilize the data and/or adopt the simplifying assumptions made in the global application (Hallegatte et al., 2016a). The estimation algorithm used in the global application[24] was accordingly modified to suit the regional level application in the Philippines.

[23] Equation 1 simplifies to Equation 12.
[24] The algorithm for the global application can be found in github.com/adrivsh/resilience_indicator_public/ (Hallegatte et al., 2016b)

4.2.1 Hazard

We use the protection level for flood hazards expressed in terms of the return period of the associated rainfall volume. We compute the probability for the protection level to be exceeded, and use it as the indicator for hazard in Equation 12. We adopt the widely-used simplifying assumption that when the flood protection is exceeded, the flood experienced is similar to that experienced without any protection (Hallegatte et al., 2016b; Jongman, Ward, & Aerts, 2012). As in the global application, we use data from FLOPROS, which stands for Flood Protection Standards, a database on flood protection expressed in terms of return period at various spatial scales (Scussolini et al., 2016).

4.2.2 Exposure of assets used

In the absence of spatial data on assets, we estimate asset exposure from the spatial distribution of the population. To do this, we overlay the population map from WorldPop with the flood hazard map from GLOFRIS. WorldPop provides population estimates per 100m square grid[25]. GLOFRIS, which stands for Global Flood with IMAGE Scenarios, provides quick risk assessment on river floods (Winsemius et al., 2015).

As shown in Table 1, the computed population exposure is disaggregated into the exposure for poor and for non-poor families using the assumed poverty exposure differential of 20% and regional level poverty incidence among families. The disaggregated exposure rate is then applied to the number of poor and non-poor families to obtain the number of exposed poor and non-poor families. Poverty data is from the Philippines' 2012 Full Year Official Poverty Statistics, and the number of families is from the 2012 Family Income and Expenditure Survey (FIES) (PSA, 2012b, 2013).

4.2.3 Socioeconomic Vulnerability and Resilience

Data for each variable on socioeconomic vulnerability and resilience are likewise disaggregated into the poor and non-poor. Except for the data on poverty, the rest of the socioeconomic variables we use are from the 2012 FIES. Income is based on data on family income per region. In terms of transfers or shared income, we use the percentage of income from other sources and other receipts to the average regional family income. Meanwhile, we assume that scaled-up social protection (i.e. diversified income) is 5% of regional average income in the aftermath of disasters. [26].

Due to the absence of a comprehensive dataset on inventory of assets and their respective users in the Philippines, the vulnerability of the assets used by families is estimated based on housing

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[25] The dataset is downloaded from www.worldpop.org.uk.

[26] The global model uses ASPIRE data as proxy of asset diversification, and an indicator under the fifth priority action under the Hyogo Framework for Action (on availability of fund to finance disaster response and recovery). Thus, the algorithm for the global model was adjusted to suit the data used in our Philippine application.

structures. We use the data of houses classified according to construction materials used for roof and outer wall: 1) “strong/mixed but predominantly strong materials”; 2) “light/mixed but predominantly light materials”; and, 3) “salvaged/mixed but predominantly salvaged materials” (PSA, 2012b). These are then matched to a damage function that assigns the following percentage of damage to flood-affected assets: high – 10%, medium – 30%, and low- 70%, (Hallegatte et al., 2016b; Hallegatte & Przyluski, 2010).

Further, we adopt the assumption that access to early warning systems reduce asset losses by 20%. This is because families have some time to prepare and undertake some mitigation actions to protect their assets as they are forewarned. As a proxy indicator for access to early warning systems, we use the proportion of families with access to mobile phone, landlines, and internet services[27].

We compute the country-level average productivity of capital as the quotient of the output and total reproducible capital from the World Penn Table (Feenstra, Inklaar, & Timmer, 2015) estimated at 32% in 2012. We use this uniform value across all 18 regions, i.e., μ=32%. Meanwhile, we assume that 95% of the damaged capital is reconstructed after three years (i.e., N=3). We use the Philippines' social discount rate of 15% (ICC, 2012) in discounting the streams of income and consumption over the 3-year period of reconstruction, i.e. ρ=15%.

4.3 Descriptive statistics

Table 5 below shows the descriptive statistics of the input indicators used in the assessment. All values are for the whole year of 2012, and are at the regional level, unless otherwise stated.

Table 5. Descriptive Statistics

Variable	Mean	Std. Dev	Min	Max
Number of families, regional average	1,190,319	784,374	375,065	3,082,475
Average family income, region (in PhP '000)	235	59	130	379
Average family income, poor (in PhP '000)	88	11	71	113
Average family income, non-poor (in PhP '000)	263	49	167	386
Poverty incidence (%)	19.7	11.9	2.6	48.7
Exposure, poor (%)	3.3	2.3	0.5	9.2
Exposure, non-poor (%)	2.7	1.8	0.5	7.1
Protection (years) (%)	9	3.9	6	24
Asset vulnerability, poor (%)	21.6	4.5	14.4	30.8
Asset vulnerability, non-poor (%)	14.3	2.8	11.1	19.7

[27] The global model uses data from the reports of countries along their progress towards attaining the priority actions under Hyogo Framework for Action, particularly the second priority action that is on early warning systems for various hazards (Hallegatte et al., 2016c). Thus, Philippines algorithm for this part is a modified version used in the global application.

Variable	Mean	Std. Dev	Min	Max
Access to early warning, poor (%)	6	2.7	2.1	12.1
Access to early warning, non-poor (%)	17.3	4.1	7.8	23.7
Social transfers, poor (%)	13	3.1	6.3	19.4
Social transfer, non-poor (%)	19.6	4.7	8.7	28.4

Note: Exchange rate in 2012 is PhP1 = USD 0.0243.
Mean is the national average or the weighted mean of the regional values (expect for the number of families).

On average, there are 1.2 million families per region. Across regions, there is wide heterogeneity in terms of the number of families, which range from 375 thousand (Cordillera Administrative Region, CAR) to over 3 million families (National Capital Region, NCR).

The average family income across the regions gives an indication of the disparity in the level of development within the country. Average family income in the regions ranges from a low of PhP130 thousand or USD3,159 (ARMM) to a high of PhP379 thousand or USD9,210 (NCR).[28] Average family income at the national level is PhP235 thousand (or USD5,711).

Among poor families, average income ranges from PhP71 thousand or USD 1,725 (Negros Island Region) to PhP113 thousand or USD2,746 (NCR). That of non-poor families ranges from PhP167 thousand or USD4,058 (ARMM) to PhP386 thousand or USD9,380 (NCR). The average family income of the poor is PhP88 thousand (USD2,138), only a little over a third of the average income of non-poor families (PhP263 thousand or USD6,391), a glaring manifestation of the highly unequal distribution of income among families in the country.[29]

Poverty incidence among families has remained high at 19.7% in 2012. Across regions, poverty incidence among families ranges from a low of 2.6% (NCR) to a high of 48.7% (ARMM).

The estimated exposure rate to riverine flood hazards among poor families ranges from 0.5% to 9.2% across regions, while that among non-poor, from 0.5% to 7.1%. Average exposure is 3.3% among poor families, and 2.7% among non-poor families.[30] Meanwhile, hazard protection among

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[28] Family income values in Table 1 are expressed in their US dollar equivalent using the exchange rate in 2012 of PhP1 = USD 0.0243.

[29] In 2015, the Gini coefficient of the Philippines was 0.4439 (PSA, 2015a). It is interesting to note that the regions that have the highest income disparity between the poor and non-poor are also the largest in terms of economic size. In the National Capital Region, which contributes about a third of the country's GDP, the average annual income of non-poor families is 3.4 times that of poor families. In Region IV-A, which is contiguous to NCR and makes the second highest contribution to GDP, the non-poor families' average income is 3.23 times that of the non-poor. Both NCR and the Region IV-A are in the Luzon island group. Similarly, Region VII, where the country's second largest city (Cebu City) is also located and which is located in the Visayas, the average family income of the non-poor is 3.29 times that of the poor. Region X where the country's fourth largest city (Cagayan de Oro City) is located Mindanao, the average income of non-poor families is 3.18 times that of poor families. The extent of income disparity in family income is same as that for the Cordillera Administrative Region (CAR) in Luzon.

[30] As in the protection level, exposure rate was generated per province and averaged to the regional level. For provinces without generated data, exposure is set equal to 5%, the lowest exposure rate across provinces that have data.

the regions range from an equivalent return period of 7 years to 24 years for the rainfall volume associated with riverine floods.[31] Across regions, average protection is equivalent to a 9-year rainfall return period.

Asset vulnerability among poor families ranges from 14.4% to 30.8%, while that of non-poor families, ranges from 11.1% to 19.7%. Average asset vulnerability is 21.6% for poor families and 14.3% for non-poor families. Among the poor families, access to early warning services ranges from 2.1% to 12.1% across regions, while among non-poor families, access ranges from 7.8% to 23.7%. Average access among the poor is only about a third that of the non-poor (6% vs 17.3%). Meanwhile, among the non-poor, an average of 19.6% of the family income comes from social transfers; among the poor, the average is 13%.

5 Results and Discussions

5.1 Asset Risk, Welfare Risk, and Resilience

Table 6 below shows the three main outputs from the model: asset risk, welfare risk, and resilience. Asset risk and welfare risk are per family, and are expressed as a percentage of the regional average annual income per family. Across regions, asset risk ranges from 0.01% to 0.62%, while welfare risk ranges from 0.02% to 1.75%.

Region I has both the lowest estimated asset risk and welfare risk. This can be largely attributed to the region's hazard protection level that is equivalent to a 24-year hazard return period. This is the highest among the regions, and is almost three times the national average. Furthermore, among the regions, Region I has the third lowest exposure rate, both among the poor and non-poor families. The region is also among the five least poor regions, as measured by poverty incidence. So, it has the lowest hazard, as well as low exposure and low vulnerability.

Meanwhile, Region VIII has both the highest estimated asset and welfare risk. Among the contributory factors are as follows: highest level of exposure both among the poor and non-poor families across 18 regions, second highest poverty incidence, and second lowest protection level.

[31] Protection level was generated per province and averaged to the regional level. For provinces without generated data, protection level is set equal to the lowest protection level across provinces that have data.

Table 6. Asset Risk, Welfare Risk, and Resilience (%)

Region	Asset Risk	Welfare Risk	Resilience
NCR - National Capital Region	0.12	0.07	165
Region IVA - CALABARZON	0.07	0.07	100
Region III - Central Luzon	0.03	0.03	88
CAR - Cordillera Administrative Region	0.02	0.03	83
Region I - Ilocos Region	0.01	0.02	61
Region VI - Western Visayas	0.35	0.58	60
Region VII - Central Visayas	0.27	0.46	59
Region II - Cagayan Valley	0.04	0.08	56
Region XI - Davao Region	0.18	0.38	47
Region X - Northern Mindanao	0.23	0.52	45
Region XIII - Caraga Region	0.20	0.46	44
Region IVB - MIMAROPA	0.53	1.21	44
Negros Island Region	0.18	0.45	39
Region V - Bicol Region	0.22	0.56	39
Region IX - Zamboanga Peninsula	0.14	0.39	36
Region VIII - Eastern Visayas	0.62	1.75	35
Region XII - SOCCSKARGEN	0.09	0.27	34
ARMM - Autonomous Region of Muslim Mindanao	0.32	1.05	31

Given the range of values for asset and welfare risks, resilience across regions ranges from a low of 31% to a high of 165%. Only two of the 18 regions reached at least a 100% resilience level: National Capital Region (NCR) and Region IV-A. The NCR is the most resilient at 165%. This implies that the region's post-disaster support is, on average, more than enough to offset the losses incurred by the affected families in NCR. As such, affected families in NCR may even be able to rebuild their lives to a better state than that prior to the disaster. Moreover, the region also has a very low poverty incidence of only 2.62%. Not surprisingly, Region IV-A, which is adjacent to the NCR, has a resilience level of 100%, indicating that asset risk is just a little above welfare risk. Region IV-A is next to the NCR in terms of lowest poverty incidence.

Of the bottom five regions in terms of estimated resilience, three are in the southern Mindanao island group, and one region each in the Visayas and Luzon groups. The ARMM that is located in Mindanao has the lowest resilience with 31%. This means that for every peso in asset losses translates to over three pesos in welfare losses. Practically what the NCR has in abundance, the ARMM has little of. Almost half of the families in the ARMM are poor, with poverty incidence of 48.70%. As noted earlier, the average income in ARMM is just over a third that of NCR's, and less than two thirds of the national average. Furthermore, the ARMM has the lowest access to social protection, where the levels of access among the region's poor (6.29%) and non-poor (8.71%)

families are less than half of the national average access to social protection among poor families (13.33%), and non-poor families (19.34%).

Region XII that is also located in Mindanao has the second lowest estimated resilience, at 34%. Over a third of the total number of families in the region are poor. Average income of families is less than half that of the NCR, and substantially lower than the average across regions.

It is worthwhile to note that all six Mindanao regions have welfare risks that are more than double the asset risks, thus resilience of each is less than 50%. Relative to regions elsewhere in the country, Mindanao experiences fewer disasters brought by natural hazards. However, relative to Luzon and Visayas, Mindanao is lagging behind in terms of access to economic and social services.

Furthermore, we note that there are regions whose level of resilience is similar but they have different levels of exposure and vulnerability. This implies that these regions will likely require different interventions aimed to reduce risk. The choice of policies to reduce risk does not depend only on resilience, but also on exposure and vulnerability.

5.2 Priority Regions

We attempt to provide broad yet useful inputs into the various stages of the development planning cycle in the Philippines. Particularly after the passage of the country's landmark laws on climate change adaptation (CCA), and on disaster risk reduction and management (DRRM) in 2009 and 2010, respectively, the country has been intensifying its efforts to integrate CCA and DRRM into each stage of the planning cycle. Our results add value into each of these stages by ensuring disaster welfare impacts and resilience can be considered.

Our results can be used to determine the regions that are in most need for development interventions to reduce/avoid welfare losses and strengthen resilience. Given the limits of the Philippines' fiscal resources for many of its development needs, there is need to direct resources to areas where they will yield the greatest net benefits.

We categorize the regions based on two criteria. The first is based on the estimated resilience, and the second is based on estimated welfare risk. We adopt three tiers per categorization, namely: low, medium, and high. We use quantiles that divides the range of values of resilience and welfare risk into intervals with unequal size but with equal number of regions per tier. The results are shown in Figures 3 and 4. There are six regions with low level of resilience: one in Luzon (Region V), two in Visayas (Region VIII and NIR), and 3 in Mindanao (ARMM, Region IX and Region XII). There are five regions with high level of resilience, all of which are in Luzon. Meanwhile, there is one region per island group that has high welfare risk. The five regions with high resilience are also the same regions with low welfare risk.

Based on these categorization results, we identify regions that may be given the highest and the lowest priority in terms of reducing welfare losses and improving resilience to disasters. Figure 5 shows as High Priority those regions with both low resilience and high welfare risk. Low Priority regions are those with both high level of resilience and low welfare risk.

Three regions are High Priority: Regions V in Luzon, Region VIII in Visayas, and ARMM in Mindanao. A distinct common characteristic of these regions is that they are among the country's poorest regions. The ARMM and Region VIII are the two poorest regions, measured in terms of poverty incidence. Region V is the poorest in the country, measured in terms of number of poor families. These regions may be considered as the top priority regions for building and/or strengthening disaster resilience.

Meanwhile, five regions have the ideal combination of low welfare risk and high resilience, and, thus may be given the lowest level of priority. These regions are NCR, CAR, I, III, and IV-A. All five regions belong to the northern Luzon area. Their relatively better hazard protection makes them more resilient than the rest of the regions despite the greater frequency of tropical cyclones that cause riverine floods in the northern part of the country.

We undertake both qualitative and quantitative examination of the robustness of our prioritization results above. As a first test, we compare our results with the categorization of provinces as contained in the country's national development plan[32] (NEDA, 2014). We note that as part of the efforts to mainstream DRRM and CCA into the development process, the country's national development plan categorized provinces based on vulnerability and risk to disasters. Provinces were likewise categorized according to poverty incidence given that poverty persists, thus poverty eradication remains a major development goal.

We find that provinces in Regions V and VIII, two of the regions we identified as High Priority, are included in the Category 3 provinces, which the national plan indicated as among those that face the greatest risk of disasters. We note, however, that our findings reveal that ARMM, which is one of the country's poorest, also faces great adverse disaster impacts in terms of welfare losses. This can be considered as an added-value of our analysis. Likewise, we find that half of the Category 2 provinces

[32] This refers to the Medium-Term Philippine Development Plan, 2011-2016. At the time that this study was started in early 2015, the said plan underwent a mid-term review in 2014. It is due to be updated again by the end of 2016; thus, the results of our assessment approach can be used to the said updating.

(or provinces with the highest poverty incidence) are located in the three High Priority regions we identified (i.e. Region V, Region VIII, and ARMM).

It has been argued earlier that resilience is significantly associated with poverty incidence. Thus, we would expect that areas where there is high concentration of poverty are also areas where there is greater need for resilience building. To check this, we conduct a spatial statistical analysis using finer-grained data, i.e. provincial values. We use the Hot Spots Analysis tool of GIS to identify regions where there is significant clustering of provinces with high incidence of poverty (hot spots), and low incidence of poverty (cold spots).[33] This is important because we use as our level of analysis the regions in the Philippines that formed from the aggregation of provinces. At times the higher-level aggregation (in this case, the regions) masks the differences in the lower spatial units (in this case, the provinces) that comprise it.

Figure 6 shows the Hot Spots Analysis result for poverty incidence. It can be gleaned that all provinces in ARMM are Hot Spots for poverty at the 99% confidence, and the provinces in Region VIII are Hot Spot at either 95% or 90% confidence. We note that these are also two of the three regions that posted the highest welfare risk and lowest resilience across all regions, and which we classified as High Priority regions.

We see that the provinces in Region X are Hot Spots either at the 99% or 95% confidence level, and the Province of Davao del Norte in Region XI is a Hot Spot at 90% confidence. Both of these regions have medium level of socioeconomic resilience.

Meanwhile, the districts[34] of NCR, and the provinces in Region III are all Cold Spots for poverty at the 99% confidence, and provinces in Region IV-A are Cold Spots either at the 99% or 95% confidence. Cold spots are where there is significant clustering of provinces with low incidence of poverty. We note that these Cold Spots shown in Figure 6 are three of the five Low Priority regions we identified.

[33] Hot Spot Analysis Tool calculates for each feature (which in the case of our analysis is a province) in the dataset a statistic called Getis-Ord Gi*. Corresponding z-scores and p-values are all calculated, where the former are standard deviations and the latter are the probabilities that the spatial clustering is a result of a random process. These scores and values indicate where there is spatial clustering of features with either high or low values of a given variable or indicator (which in our analysis is poverty incidence). For z-scores that are positive and statistically significant, the higher the z-score, the greater is the intensity of clustering of provinces with high values (hot spot). Conversely, for z-scores that are negative and statistically significant, the lower the z-score, the greater is the intensity of clustering of provinces with low values (cold spot). This tool evaluates a feature relative to its neighboring features. A feature can have high value of a given variable but not necessarily a hot spot. For a feature to be a statistically significant hot spot, it must have a high value of the variable and be surrounded by features with also high values of the same variable. Thus, in this case of the analysis we undertake, for a province to be a statistically significant poverty hot spot (cold spot), it must have high (low) poverty incidence and be surrounded by provinces with high (low) poverty incidence. (This is a modified explanation from http://desktop.arcgis.com)

[34] The National Capital Region do not have provinces, only districts. Like the provinces, districts comprise of cities and municipalities. A province is one of the administrative divisions in the Philippines, and is ran by a governor. A district is created for the purpose of representation to the House of Representatives.

Overall, our results show that regions with the lowest resilience and highest welfare risk are also the country's poorest regions, either in terms of incidence of poverty or number of poor persons. On the other hand, regions with highest resilience and lowest welfare risk are the country's most socioeconomically-advanced regions. These results suggest that poverty reduction and disaster risk reduction, including through resilience building, are connected rather than discrete development concerns. Thus, development planning that addresses poverty, economic welfare, and disaster risk in an integrated manner translates to greater effectiveness in addressing each concern, as well as greater efficiency in resource use.

Figure 3. Categorization of Regions According to Resilience

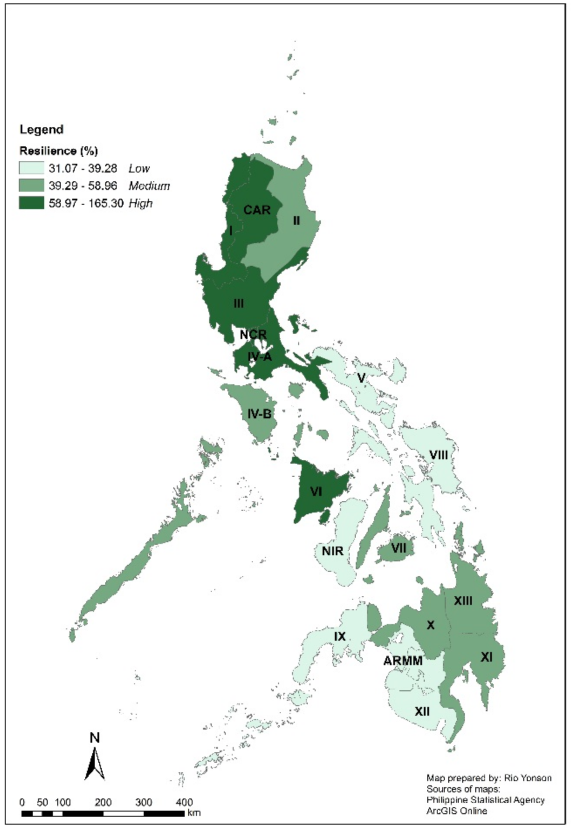


Figure 4. Categorization of Regions According to Welfare Risk

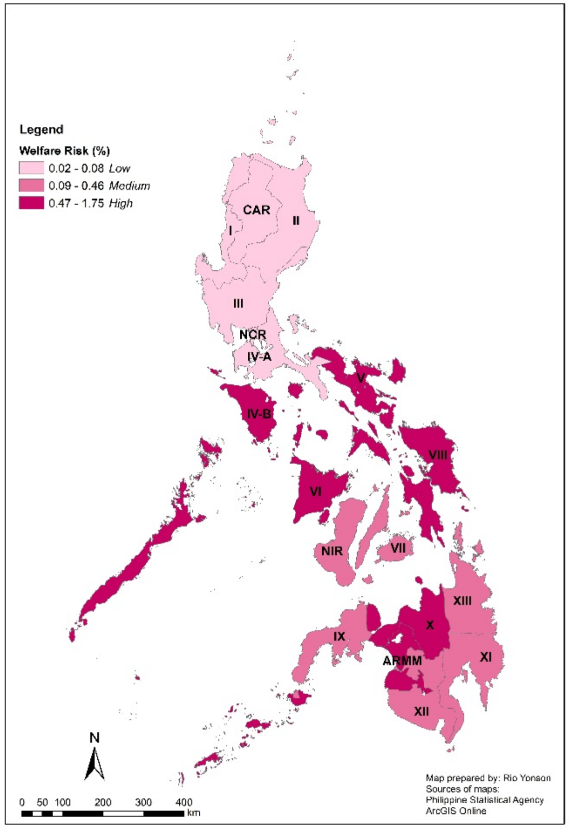


Figure 5. Prioritization of Regions, Based on Resilience and Welfare Risk

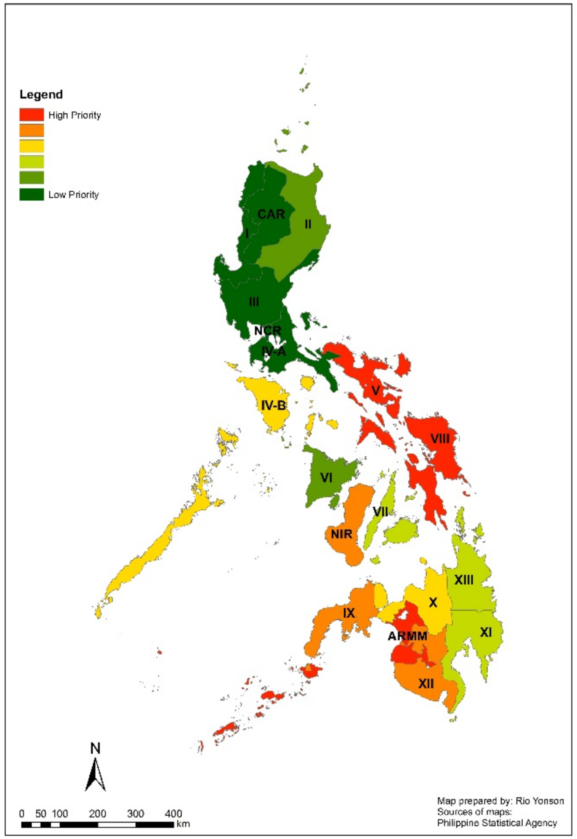
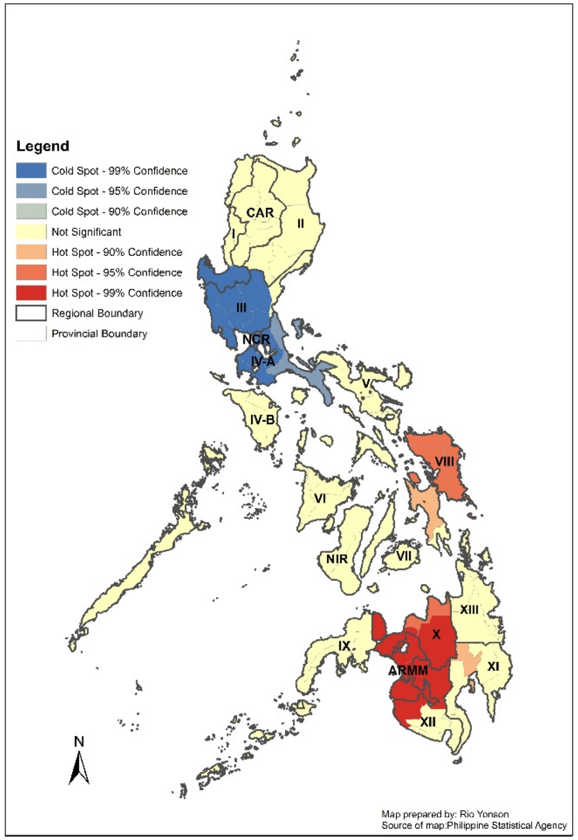


Figure 6. Hot Spot Analysis of Provincial Level of Poverty Incidence



5.3 Policy Experiments

We undertake policy experiments to provide a systematically derived basis for the prioritization of alternative policy options within each region, and across regions. We adjust, one at a time, the value of selected input variables from their respective values under the base case scenario presented in Sections 5.1 and 5.2.

- Hazard Protection
  - Protection level equivalent to one year higher than the current level
-
- Exposure
  - 10% reduction in the exposure of poor families
  - 10% reduction in the exposure of non-poor families
  -
- Vulnerability and Resilience
  - 5% reduction in the asset vulnerability of poor families
  - 5% reduction in the asset vulnerability of non-poor families
  - Time to reconstruct is shorter by 1 year
  - 1% reduction in poverty incidence
  - 10% increase in access to early warning among poor families
  - 10% increase in access to early warning among non-poor families
  - 5% increase in reactivity to early warning
  - 5% increase in social protection for poor families
  - 5% increase in social protection for non-poor families
  - 15% increase in the scale-up of social protection for poor families
  - 15% increase in the scale-up of social protection for non-poor families
  - 10% increase in income of poor families
  - 10% increase in income of non-poor families
  - 10% increase in average income of families

The outputs are policy cards for each of the 18 regions of the Philippines. The policy card has at least two purposes: one, as a tool to track regional level progress; and, two as menu of policy options prioritized according to their effectiveness in reducing asset and welfare risk, and increasing resilience per region.

In Section 5.3.2, we also use the assessment approach to determine in which regions a particular policy alternative will yield the greatest and least impacts in terms of reduction in welfare and asset losses. Unlike in a cross-national assessment, our intra-national analysis allows us to safely assume that the costs of implementing these policies from one region to another are comparable.[35] Thus, even if we do not measure these costs, it makes sense to discuss which regions will benefit the most

[35] This is generally true except for NCR and ARMM. Data on building construction cost per square meter in 2013 show that for the 16 regions (i.e. excluding NCR and ARMM) the cost range from USD 170 to USD 260. However, for ARMM, it is only USD 95. For NCR, it is over USD 300. The minimum wage is also substantially higher in NCR than in the other 17 regions.

from each policy alternative. We measure benefits (or the gains) in terms of reduction in asset losses and welfare losses. We also remind the readers that our analysis is only for a single hazard, i.e. flood. However, a number of the policies we consider have benefits across hazard types and will increase resilience over multiple hazard dimensions. As such, our single hazard assessment under-estimates the benefits from these policies.

5.3.1 Within Each Region

We perform the exercise for each region to estimate the effect of the policy alternatives on total regional welfare losses and asset losses. For brevity, we focus our analysis on one High Priority (ARMM), and on one Low Priority (NCR) region presented in Section 5.2. The policy cards of the regions are juxtaposed in Figures 7 and 8.

For ARMM, it is the 10% reduction in the exposure of poor families that consistently yield the highest reduction in welfare losses and asset losses, respectively. Meanwhile, for NCR it is the 10% reduction in the exposure of non-poor families that yield the highest gains in terms of reduction in both asset and welfare losses.

Similarly, we find that for ARMM, between reducing asset vulnerability of the poor and of the non-poor, it is the former that results in greater reduction in welfare losses. The same situation is observed for the other High Priority Regions, such as Regions VIII and V.

The converse is seen for NCR, where it is the reduction in asset vulnerability that generates greater reduction in welfare losses, as well as in asset losses. This is also observed for CAR and Region IV-A, which like NCR are Low Priority Regions.

We also see that while the 10% reduction in exposure among the poor and the non-poor are the two top gain-yielding policy alternatives for ARMM, it is the 10% reduction in exposure among the non-poor families and the 5% reduction in the asset vulnerability for non-poor families that are the top two policies for NCR. In fact, across all regions, it is only the NCR that has 5% reduction asset vulnerability within the first two among the policy alternatives; the rest of the regions have 10% exposure of the poor and the non-poor as the top two.

The above results together suggest that while there are similarities in the ranking of policies among regions with comparable levels of resilience and welfare risk, we find that the ranking of priorities vary from one region to another. This suggests that there are region-specific conditions that influence welfare impacts and resilience. Thus, the need for region-specific policies and interventions, as well.

Figure 7. Policy Cards for a High Priority Region: ARMM

Figure 8. Policy Cards for the Low Priority Regions: NCR

5.3.2 Across Regions

We also use the assessment approach to determine in which regions a particular policy alternative will yield the greatest and least impacts in terms of reduction in welfare and asset losses. Unlike in a cross-national assessment, our intra-national analysis allows us to safely assume that the costs of implementing these policies from one region to another are comparable. Thus, even if we do not measure these costs, it makes sense to discuss which regions will benefit the most from each policy alternative. We measure benefits (or the gains) in terms of reduction in asset losses and welfare losses.

5.3.2.1 Reduction in exposure by 10%

It can be gleaned from Figure 9 that across the regions, a 10% reduction of exposure among the poor families results in reduction in annual welfare losses ranging from PhP170 million (CAR and Region I) to PhP1.9billion (Region VIII), and asset losses from PhP31 million (Region I) to PhP300 million (Region VIII). On the other hand, reducing exposure among the non-poor by 10% results in reduction in welfare losses ranging from PhP360 million (CAR) to PhP2.7 billion (NCR).

Compared with the results for the non-poor, we see that for the poor families, there is a wider difference between the reduction in asset losses and welfare losses. This is because the poor have very few assets, hence it is expected that reduction in asset losses will be much lower than the reduction in welfare losses. It is also noted that among the non-poor, the reduction in asset losses is greater than the reduction in welfare losses. The reverse is true among the poor.

Moreover, the comparison of magnitude of effects between reducing exposure among the poor and exposure among the non-poor reveals that the latter yields a higher total reduction in welfare losses across regions (PhP1.9 Billion vs PhP2.7 billion). However, it will be recalled that despite the high incidence of poverty, there are still more non-poor families. Thus, when expressed on a per family basis, there is greater reduction in welfare losses when exposure of the poor is reduced, than exposure of the non-poor.

5.3.2.2 Reduction in asset vulnerability by 5%

Reducing by 5% the asset vulnerability of the poor reduces welfare losses and asset losses in Region VIII by PhP340 million and PhP54 per year, respectively, the highest across all regions (Figure 10). As poor families have very few assets, the reduction in asset losses is considerably lower than the reduction in welfare losses. The next eight regions that follow Region VIII have comparable reductions in welfare losses, though the reduction in each region is notably less than half of that in Region VIII.

On the other hand, reducing by 5% the asset vulnerability for non-poor families benefits NCR the most, both in terms of reductions in asset losses and welfare losses. Expectedly, given a much larger asset base, the reduction in asset losses in NCR of PhP600 million per year is substantially higher than those in the rest of the regions, which range from PhP8.7 million per year (CAR) to PhP220 million per year (Region VIII).

5.3.2.3 Increase in average income by 10%

Meanwhile, as shown in Figure 11, a 10% increase in the average income of the poor again benefits Region VIII the most, and followed by Region IV-B. Interestingly, we find that ARMM, which has the highest poverty incidence among the regions, is only the 9th to gain. This reflects the fact that many of the ARMM's poor earn very low incomes such that a 10% income increase does not translate to welfare gains comparable to other areas with high poverty incidence. Nonetheless, within ARMM, the reduction in welfare losses largely offsets the increase in asset losses. The gains in welfare (absolute value of reduction in welfare losses is PhP0.26 million per year) is double that of the value of the asset losses (PhP0.11 million pesos per year).

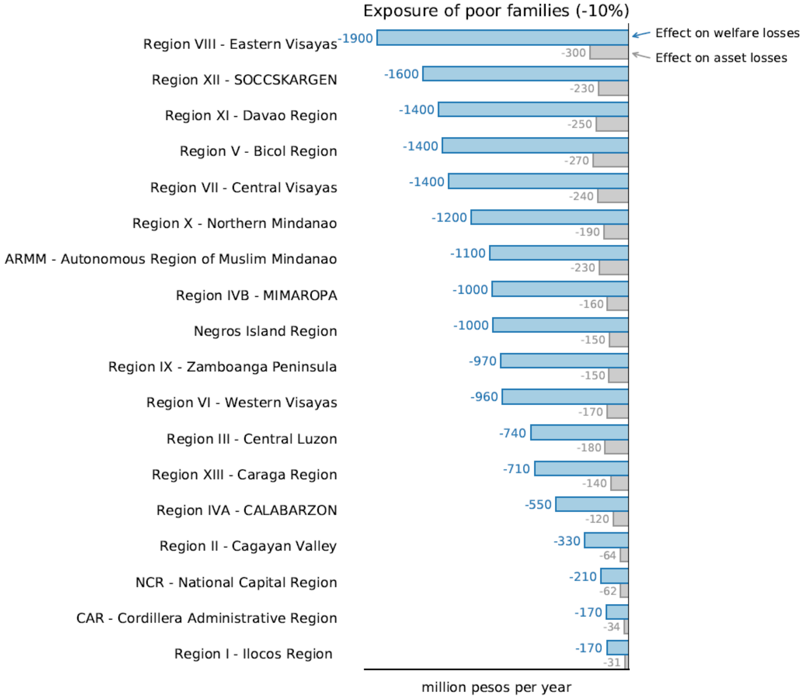
Meanwhile, a 10% increase in the average income of the non-poor will likewise benefit Region VIII the most. The least to gain in either of the policy alternatives of reducing exposure are CAR and Regions I, II and III. It will be recalled that all these are under the Low Priority regions identified earlier in Section 5.2.

5.3.2.4 Reduction in poverty incidence by 1%

Figure 12 shows the result of implementing a uniform 1% decline in poverty incidence in each of the 18 regions. Expectedly, such policy will have the greatest impact in terms of reducing welfare losses in Region VIII, as the region has one of the highest poverty incidence and number of poor families.

Interestingly, despite having the lowest poverty incidence and number of poor families, NCR stands to gain next in terms of highest reduction in welfare losses and ARMM is only the 13th. As shown in Figure 8 earlier, a 1% reduction in poverty incidence in NCR will yield welfare gains of PhP20 million pesos compared to just PhP5.1 million for ARMM as shown in Figure 9. This indicates that while poverty is prevalent in ARMM (much more than in NCR), there are other factors that have greater influence on disaster consequences.

Figure 9. Reduction in Exposure by 10%



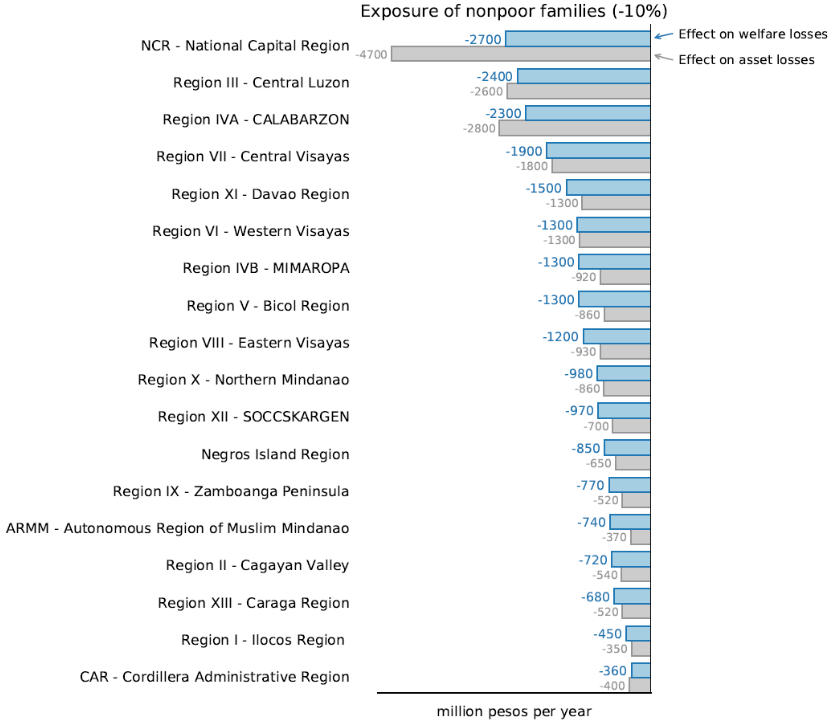
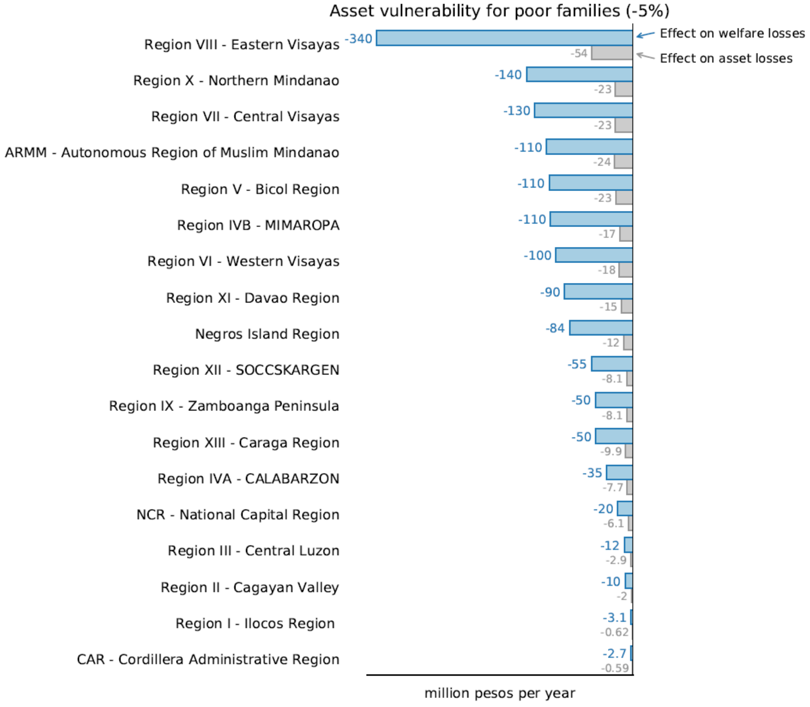


Figure 10. Reduction in Asset Vulnerability by 5%



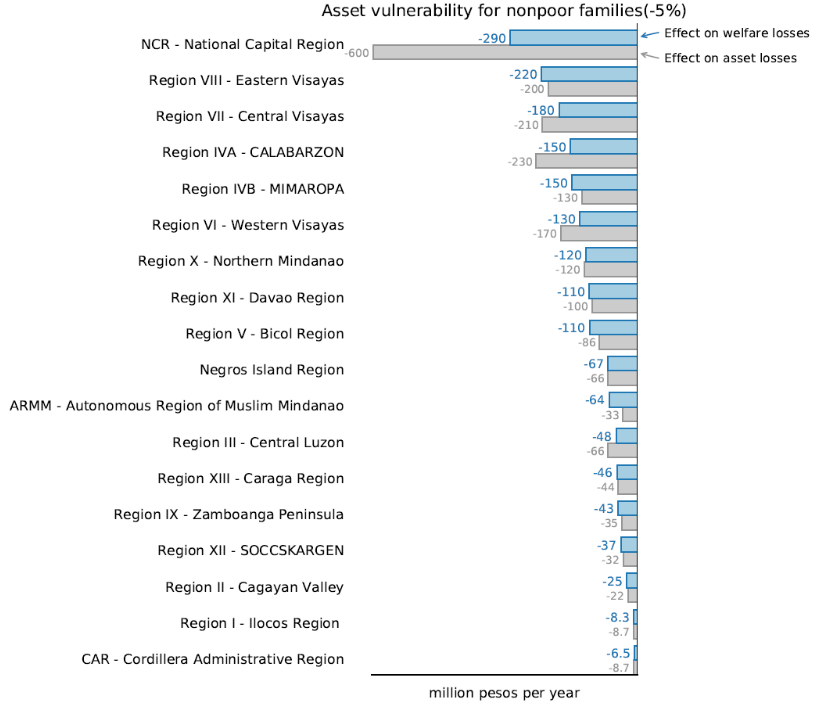


Figure 11. Increase in Family Income by 10%

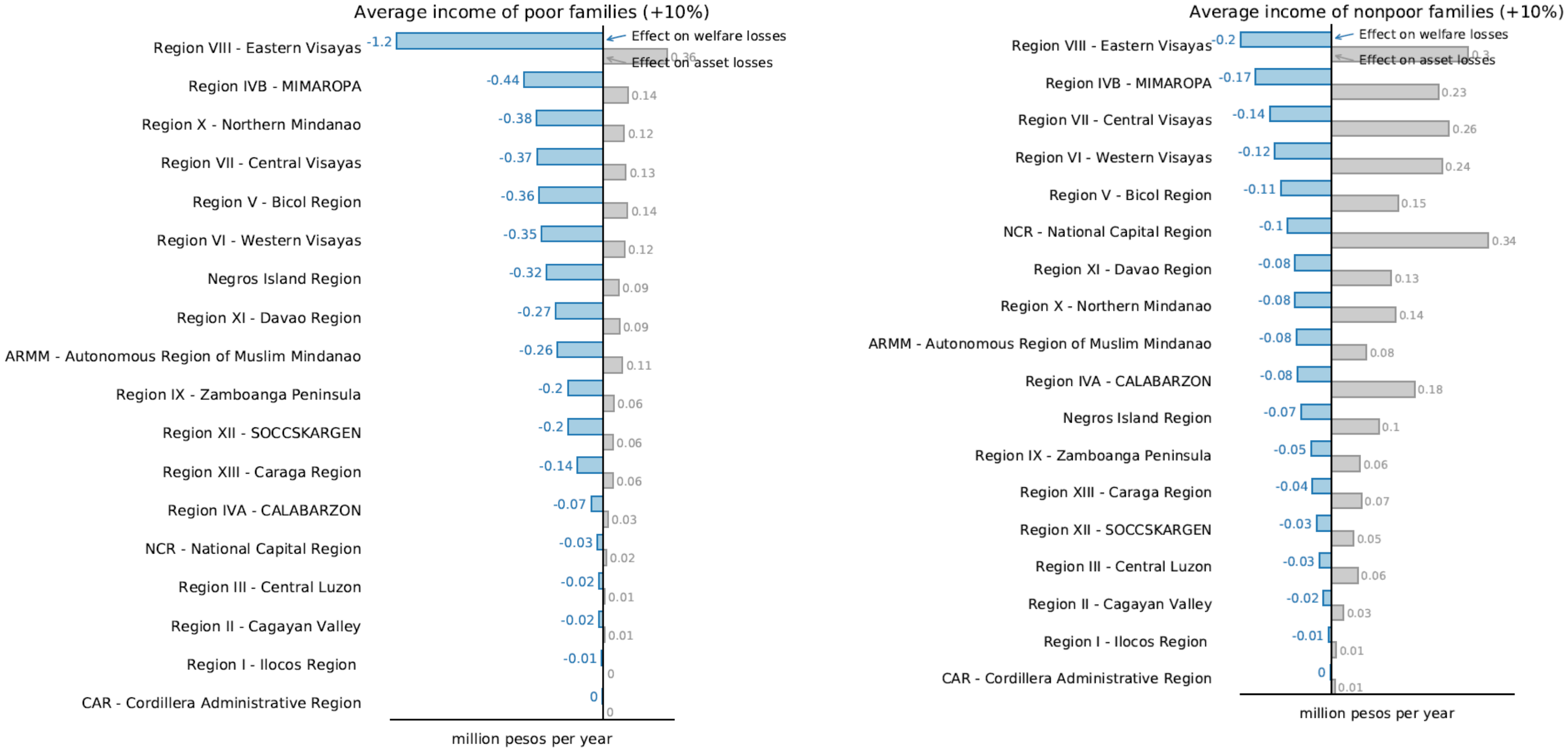
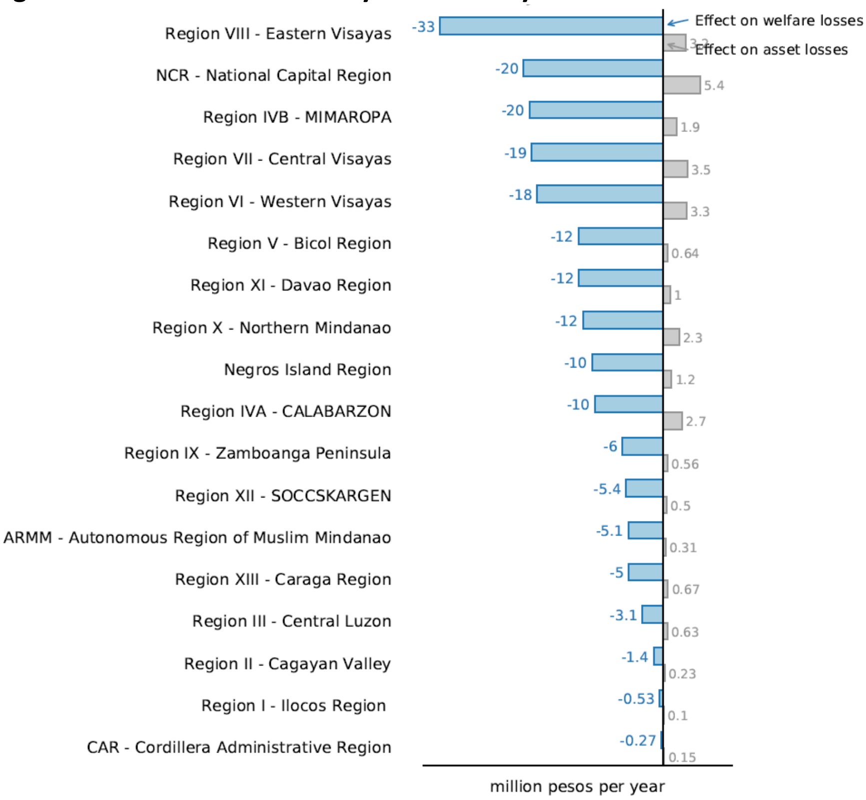


Figure 12. Reduction in Poverty Incidence by 1%



5.3.2.5 Increase in social transfers by 10%

Increasing pre-disaster social transfers for poor families will reduce post-disaster welfare losses but will not have any impact on asset losses. It is this diversification in income source and risk sharing mechanism that reduce the impact on welfare (Hallegatte et al., 2017).

As shown in Figure 13, increasing the social transfers to the poor brings the largest welfare gains again to Region VIII. Region IVB second highest gain, but welfare reduction is less than half of that for Region VIII. The Cordillera Administrative, which is among the least poor regions, stands to gain the least.

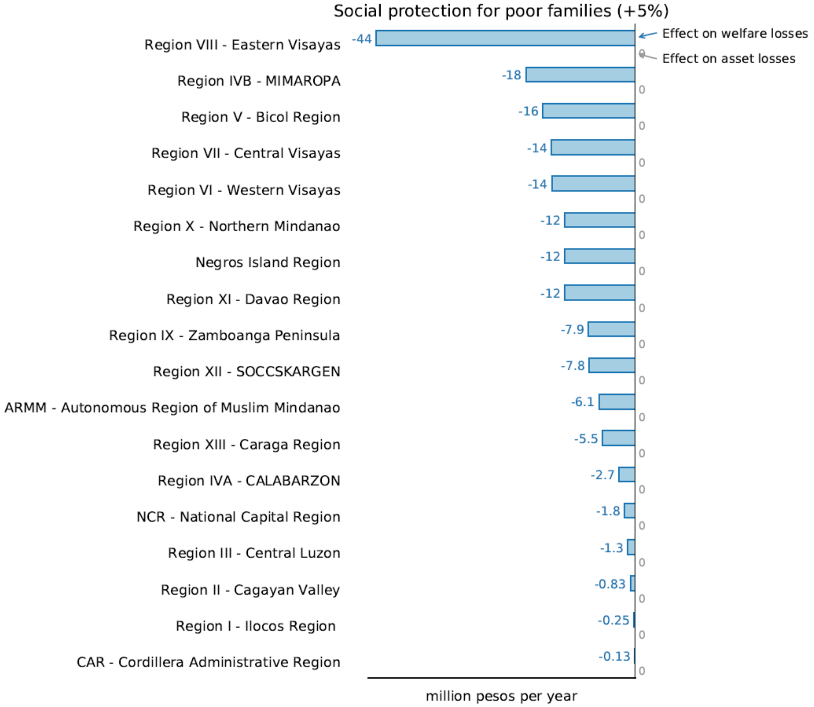
In terms of increasing social transfers for the non-poor, Regions IVB and VIII which are expected to gain the most have about the same reduction in welfare losses. It is noted however that gains from increasing social transfers for the non-poor results in much lower gains in welfare than from increasing social transfers to the poor.

5.3.2.6 Provision of scaled-up protection by 15%

Likewise, scaling up social protection does not translate to any reductions in assets losses given the ex post nature of the provision of assistance. However, there are some important gains in terms of welfare particularly when these are directed towards the poor. Scaling up social protection by 15% of regional income translates to welfare gains for Region VIII amounting to PhP110 (Figure 14). For the rest of the regions, welfare gains ranges from PhP0.35 million to PhP48 million.

On the other hand, scaling up assistance to non-poor families by the same percentage results in much lower gains in welfare and assets. Region IV-B benefits the most, is again closely followed by Region VIII.

Figure 13. Increase in Social Protection by 10%



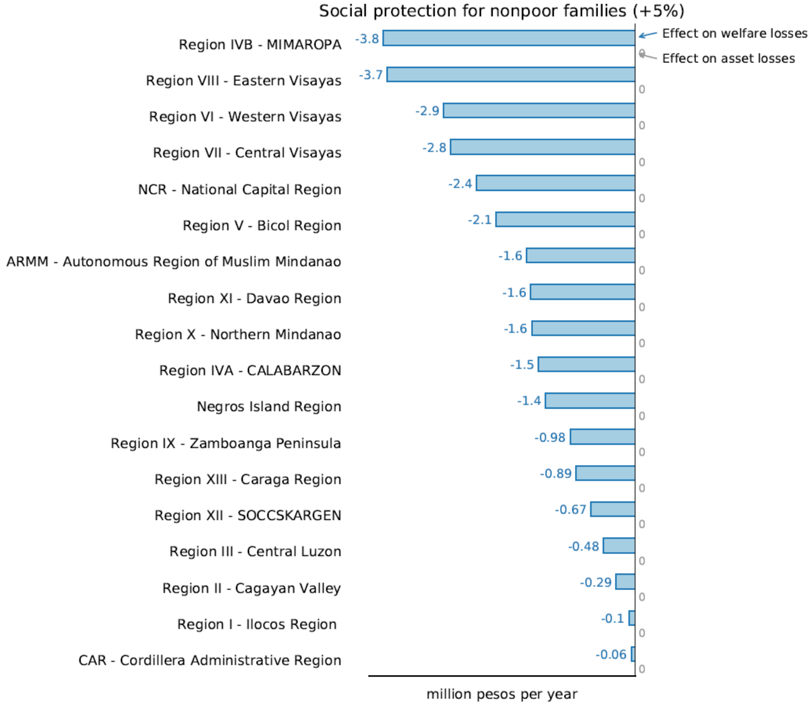
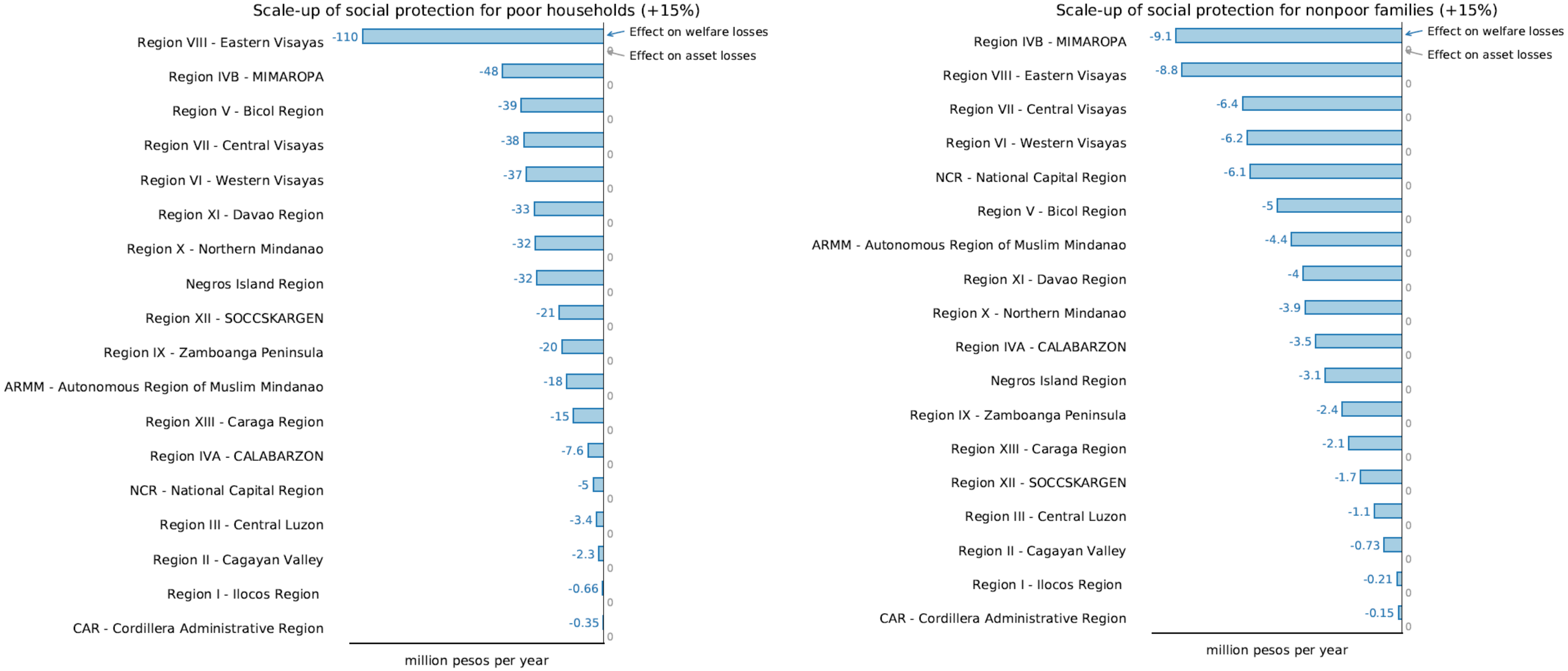


Figure 14.Provision of scale-up protection by 15% of income



From the above results, it is clear that Region VIII will stand to gain the most in terms of various interventions to affect any of the components of the welfare risk among the poor. Even for several policies for the non-poor (such as increasing the income, increasing the social protection, scale-up of protection, increasing access to early warning, reducing asset vulnerability for non-poor), Region VIII is one of the top regions expected to experience the highest reduction in welfare loss, or equivalently, the highest gains in welfare.

6 Conclusions and Caveats

This work extends the usual assessment of disaster impacts on assets by conducting an analysis of the consequent welfare impacts at the subnational level. The estimate for welfare losses along with the estimate for asset losses allows for a quantified measure of resilience to disasters. Together, these quantified impacts enable the prioritization of policy alternatives depending on the main region-specific factors that drive asset and welfare losses.

Region I has the lowest estimated asset risk and welfare risk, due to high hazard protection level, low exposure, and poverty incidence. At the opposite end is Region VIII due to high exposure both among the poor and non-poor families, high poverty incidence, and low protection level. Meanwhile, the NCR is the most resilient, while ARMM is the least resilient. The findings about these latter two regions best demonstrates the importance of risk sharing and income diversification though social transfer and public post-disaster support to minimize or avoid adverse impacts of disasters on welfare.

The categorization of regions based on estimated resilience, and estimated welfare risk suggest that Regions V and VIII, and ARMM may be considered as the top priority in terms of allocation of national public resources for strengthening disaster resilience to minimize the impacts of flood disasters on welfare. On the other hand, NCR, CAR, and Regions I, III, and IV-A may be given the lowest level of priority.

The policy experiment within each region and the comparison of results across regions reveal evident similarities in the ranking of policies among regions with comparable levels of resilience and welfare risk. Nonetheless, the ranking of priorities varies for different regions. Not surprisingly, for a majority of the policy alternatives, it is Region VIII that is expected to benefit the most. Apart from being one of the socioeconomically disadvantaged, it is also one of the regions that experienced some of the worst disaster impacts in recent decades.

Overall, our results indicate that reduction of adverse disaster impacts, including welfare losses, and reduction of poverty are generally complementary development agenda. Thus, this suggests the need to ensure an integrated approach in addressing poverty and economic disaster welfare risk.

We note some caveats. Given the limits of available data, this study covers only riverine floods. As the Philippines and its regions are also prone to other geologic and hydro-meteorological hazards, a multiple hazard analysis will be desirable. While we expect that regional levels of resilience under the multi-hazard assessment will be lower than those presented here, we expect very similar ranking of regions for other hazards as those shown in this current paper.

Another limitation of the study is that we also did not account for disaster-induced mortality and morbidity, which, despite being non-economic, also have obvious impacts on the welfare and resilience of the affected family members and other people in the community. Furthermore, we excluded from the analysis the long-term welfare impacts, such as poverty traps or intergenerational poverty (Karim & Noy, 2016; van Den Berg, 2010). Extensions to our current assessment to address the above limitation can be readily undertaken with access to needed data, and this forms part of our future research agenda.

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