

Bank Stress Testing of Physical Risks under Climate Change Macro Scenarios: Typhoon Risks to the Philippines

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Bank Stress Testing of Physical Risks under Climate Change Macro Scenarios: Typhoon Risks to the Philippines**Prepared by Stephane Hallegatte, Fabian Lipinsky, Paola Morales, Hiroko Oura, Nicola Ranger, Martijn Gert Jan Regelink, and Henk Jan Reinders**Authorized for distribution by Vikram Haksar
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ABSTRACT: Bank stress tests of climate change risks are relatively new, but are rapidly proliferating. The IMF and World Bank staff collaborated to develop an experimental macro scenario stress testing approach to examine physical risks for banks by building a dynamic stochastic general equilibrium model linked to global climate and a catastrophe risk model specifically for the Philippines. Our model shows that the impact of extremely rare typhoons on GDP could already be systemic and worsen substantially with climate change. However, bank capital declines only modestly unless the event is compounded with other disasters, partly thanks to the strength of Philippines' banks and economy before the COVID crisis. However, more work is needed before drawing strong conclusions about the relevance of climate risk, as the model focused only on typhoons' physical capital destructions and their macroeconomic-level transmissions to banks.

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WORKING PAPERS

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Glossary

AE	Advanced economy
AFC	Asian financial crisis
AR	Assessment report
BIS	Bank for International Settlements
BoE	Bank of England
CAT	Catastrophe (risk model)
CGM	Computable general equilibrium model
DNB	De Nederlandsche Bank
DSGE	Dynamic stochastic general equilibrium
ECB	European Central Bank
EMDE	Emerging market and developing economy
FSAP	Financial Sector Assessment Program
FSI	Financial Stability Institute
GCM	General circulation model
GFC	Global financial crisis
IAM	Integrated assessment model
IPCC	Intergovernmental Panel on Climate Change
LGD	Loss given default
NGFS	Network of Greening the Financial System
PAGASA	Philippines Atmospheric, Geophysical, and Astronomical Services Administration
RCM	Regional climate model
RCP	Representative Concentration Pathway
TC	Tropical cyclone
TCFD	Task Force on Climate-Related Financial Disclosures
TFP	Total factor productivity
UNEP	United Nations Environmental Programme
VaR	Value at Risk
WEO	World Economic Outlook

Executive Summary

The literature on financial stability analysis of risks from climate change is young but rapidly growing. Regulators and central banks around the world have started to warn of the impact of climate change and environmental risks on the stability and soundness of financial sectors. Through their Financial Sector Assessment Program (FSAP), the IMF and the World Bank (WB) have begun in-depth pilot assessments; academics have also initiated research in this area. Moreover, most exercises have focused on advanced economies (AEs) and global banks, while studies for emerging market and developing economies (EMDEs) have been limited, even though they are expected to be more affected by and vulnerable to climate change.

Against this backdrop, we developed a new macro scenario stress testing method for banks to assess physical risks from climate change, taking an emerging market economy—the Philippines—as an example. The Philippines is highly exposed to typhoon risks. Our approach includes four sub-modules tailored to the country: climate scenario (future projection of typhoon likelihood and intensity), disaster scenario, macro-financial scenario, and stress test modules. The climate scenario provides future typhoon likelihood and intensity under a standard global warming scenario. The disaster scenario estimates damage (loss of physical capital) from typhoon wind. The macro scenario is built on a dynamic stochastic general equilibrium (DSGE) model and calculates the impact of lost physical capital (that is, a capital depreciation shock) on the economy. Then, we estimate the impact on bank solvency using the standard IMF solvency stress testing method for banks in FSAPs.

Our approach contributes to the literature in several aspects. First, we used climate scenarios provided by an existing country-specific climate science study by the government of the Philippines. Second, we established damage functions with a strong micro-foundation using catastrophe risk model (CAT) in contrast with rather arbitrary functions used in typical integrated assessment models (IAMs). CAT models, originally developed for property insurers, are based on the science and engineering studies of natural hazards and their impacts on specific assets like buildings and infrastructure. Incorporating country-specific data on location and quality of properties, the model estimates potential losses of physical capital for events with various likelihoods. Third, we “coupled” the climate and CAT models. Typical CAT models use current climate parameters. We used the future climate parameters given by the existing government of the Philippines’ climate study to properly account for future climate change.

The results indicate that extremely rare typhoons’ impact on GDP growth could be systemic in the Philippines even now, and it would worsen substantially with climate change. Even under the current climate conditions, rare disasters with return periods—the inverse of frequency or annual probability—of 100 years or above could reduce GDP notably. With climate change, these rare typhoons could reduce GDP by 5–14 percentage points, about 40–60 percent more than now. Such a reduction of GDP is more than those reductions observed during the past financial crises. However, the economic impact is relatively small for typhoons that could occur once in 25 years or less—a tail level relevant for standard bank stress tests.

Nonetheless, bank stress tests indicate that the impact of climate change on typhoons alone may not reduce bank capital to worrisome levels unless it is compounded with other disasters. Without compounding events, climate change in the future would reduce bank capital ratio visibly only in the tail events once in 500 years. Still, the decline is small. Also, the difference in capital ratios between baseline without any major typhoons and the scenario with a 500-year return period typhoon remains minimal. These benign results partly reflect

Philippines' healthy macro-financial conditions at the start of the stress (end-2019). However, the compound risk of an extreme typhoon and, for example, a COVID-like pandemic significantly reduces bank capital.

These relatively benign results should be interpreted with caution. The exercise focuses on typhoon wind destruction alone and does not include other related climate change risks that could amplify the impacts, such as floods and sea-level rise. It excludes damages from physical risk other than infrastructure damages from typhoons due to storm wind. Furthermore, the exercise focused only on macro-economic-level transmission channels affected by severe typhoons. Due to data limitation, we did not account for possibly concentrated effects from lower property collateral values or credit risk concentration. In the Philippines, bank loan data by industry and by some measure of location are available, but not by industry and location conjoined, constraining micro-level analysis.

Despite these limitations, our results appear to be broadly comparable to the estimates under the 2021 scenarios from the Network of Greening Financial Systems (NGFS) where projections overlap. Both scenarios show that future damage rates for once-in-a-100-year typhoons increase about 30–40 percent under RCP 8.5, and the corresponding GDP impacts are about 5 percent. This finding is good news for both our and NGFS approaches, indicating the robustness and complementarity of the two different analytical strategies in this specific case and common return periods and projection horizon.

At the same time, our approach can provide richer information on tail events than the NGFS scenarios, even though it requires substantial country-specific data and climate model analyses. The NGFS scenarios offer estimates under various global emissions scenarios—not just RCP 8.5 as used in this simulation—but only for once-in-a-100-year disasters. In contrast, our scenarios provide detailed outcome across different return periods, incorporate uncertainties in the underlying climate models suited for the Philippines, and present more details of the macroeconomic and financial implications of the hazard under consideration.

It is crucial to interpret the results cautiously, given the exceptionally high level of uncertainty regarding financial and economic analyses of climate change. These analyses are constrained by significant uncertainties at all layers, including: (i) uncertainties with the link between socioeconomic activities and greenhouse gas emissions; (ii) uncertainties in climate science studies that measure the quantitative impact of emissions on global warming, and the impact of global warming on local climate-related phenomena such as typhoons and sea-levels; and (iii) uncertainties about the effects of the local climate-related phenomena on the environment and social and economic systems, and their implication on financial stability. Additionally, there are complicating and not yet well understood feedback relationships among these dynamics.

Introduction¹

The literature of financial stability analysis of risks from climate change is young but rapidly growing. Regulators and central banks—among others through the Network for Greening the Financial System (NGFS)—have started to warn of the impact of climate change and environmental risks on the stability and soundness of financial sectors (NGFS 2020a, 2020b, 2021a, and 2021b). Several major central banks and international institutions started to explore climate-change-related financial stability risks (De Nederlandsche Bank (DNB) 2017 and 2019; Reinders and others 2020; Bank of England (BoE) 2019; Batten and others 2016; Campiglio and others 2018; European Central Bank (ECB) 2021; European Banking Authority (EBA) 2021, French Autorité de contrôle prudentiel et de résolution (ACPR) 2021, Federal Reserve Bank of New York (NY Fed, Jung and others 2021), Financial Stability Institute (FSI) 2021), and Bank of Canada (BoC) and Office of the Superintendent of Financial Institutions (OSFI) 2022). The Financial Sector Assessment Program (FSAP) of the IMF, and the World Bank (WB) started in-depth pilot assessments (IMF 2019, 2020, and 2021a). FSAPs are expected to cover more analysis on climate change risks in the future (IMF 2021b, 2021c, and 2021d). Academics have also started research in this area (for example, Battiston and others 2017). Available data are increasing with quickly developing disclosure requirements and a growing number of data and model vendors (NGFS 2021c; and Task Force on Climate-related Financial Disclosures (TCFD) 2021)).

So far, most exercises have focused on advanced economies (AEs) and global banks. Transition risks are discussed for the Netherlands (Vermeulen and others 2019; Reinders and others 2020), the United Kingdom (BoE 2019), euro area countries (ECB 2021), ACPR (2021), Jung and others (2021), BoC-OSFI (2022), Norway (IMF 2020), and United Kingdom (IMF 2022). The BoE, ECB, NY Fed, ACPR, and DNB also examined physical risks (see FSI 2021 for survey). The IMF examined hurricane risks to the Bahamas, a small but high-income economy dependent upon tourism and offshore banking (IMF 2019). UNEP conducted bottom-up exercises with some global banks, examining transition risks (UNEP-Oliver Wyman 2018) and physical risks (UNEP-Acclimatise 2018). Some of the physical risk analyses are not exactly climate change scenario analyses: the ECB (2021) analyzed highly granular data to assess current, not future, physical risks; DNB (2017) examined the impact of dyke breach without assigning its likelihood.

On the other hand, studies for emerging market and developing economies (EMDEs) have been limited, even though such economies are likely to be affected more by climate change than AEs. EMDEs, especially those close to the equator, are expected to be more affected by climate change (the Intergovernmental Panel on Climate Change (IPCC) 2014 Assessment Report (AR) 5; IMF 2017), as they are more exposed to physical risks, such as tropical cyclones, drought, heat waves than are AEs. EMDEs are also more vulnerable to disasters due to the less robust quality of institutions and infrastructure. Also, smaller, less diversified economies (geographically and economically) are more likely to be systemically affected by a single extreme disaster than are large economies. For instance, one hurricane could devastate a small island economy but not a large economy like the United States. Insurance markets are also usually underdeveloped in these economies, limiting opportunities to diversify away disaster risks financially other than through international

¹ The authors thank to the support provided by FSAP management teams at the IMF, led by Vikram Haksar (especially Ivo Krznar and Pierpaolo Grippa) and at the WB, led by Cedric Mousset; the IMF country team for the Philippines, led by Thomas Helbling; and the WB Disaster Risk Financing and Insurance programme unit led by Oliver Mahul. We also appreciate the productive engagement, feedback, and support provided by officials from the government of the Philippines and the Central Bank of the Philippines.

support.² As for transition risks, small EMDEs' emissions may not be that high, but the economy could be affected by structural changes in AEs from climate policies. Nonetheless, there have to date been few climate change stress tests for EMDEs, partly because of data limitations.

Against this backdrop, we developed a new macro-scenario stress testing method for banks to assess physical risks from climate change, taking an emerging market economy—the Philippines—as an example (Figure 1). The Philippines is one of the most susceptible to climate change-related hazards, especially typhoons (IMF 2021a).³ Fortunately, there are several detailed climate science and disaster risk studies on the Philippines available for incorporation into our model. We built country-specific climate change scenarios using these studies, with three modules: climate, disaster, and macro-financial modules. The future climate scenario is based on an existing study by the government of the Philippines in collaboration with the UK's Meteorological (Met) Office. The study took the highest emission increase due to human activity (and therefore a global warming scenario)—IPCC's Representative Concentration Pathway (RCP) 8.5⁴—and downscaled it to estimate typhoon risks in the Philippines by the mid-21st century. The disaster scenario estimates damage (loss of physical capital) from typhoon wind using the catastrophe risk (CAT) model. We considered chronic damages (average impact) and extreme events with likelihoods ranging from once in 10 to 500 years.⁵ The macro scenario is built on a dynamic stochastic general equilibrium (DSGE) model calibrated for the Philippines and calculates the impact of lost physical capital (that is, a capital depreciation shock) on the economy. Then, we estimate the impact on bank solvency using the standard IMF solvency stress testing method for banks in FSAPs. Similar to central banks' pilot exercises, we do not apply any hurdle rates to decide whether a bank fails or not. Our analysis is meant to explore new techniques to better understand climate change and financial stability. It would be premature to use this model to assess the adequacy of capital for climate change and calibrate capital surcharges.

Our approach uniquely contributes to the literature by building scenarios using country-specific climate science and hazard scenario studies. Recent pilot exercises by central banks largely use existing integrated assessment models (IAMs), including those provided by the NGFS. IAMs typically have four modules: climate, impacts (or damage function), economy, and energy (see Nikas 2019 for a detailed overview).⁶ They tend to focus more on the economy and energy modules and use highly abstracted reduced form climate models. In

² In AEs, risks to disaster insurers are usually diversified internationally with global re-insurers. While the humanitarian cost of disasters could be much higher in EMDEs, the dollar value insured losses are higher in AEs, reflecting higher insurance coverage and purchasing power differences. For instance, all of [Lloyds' mandatory Realistic Disaster Scenarios](#) for insurers' disaster risk stress tests are for flood, windstorm, earthquake, and terrorism risks in the US, Europe, and Japan.

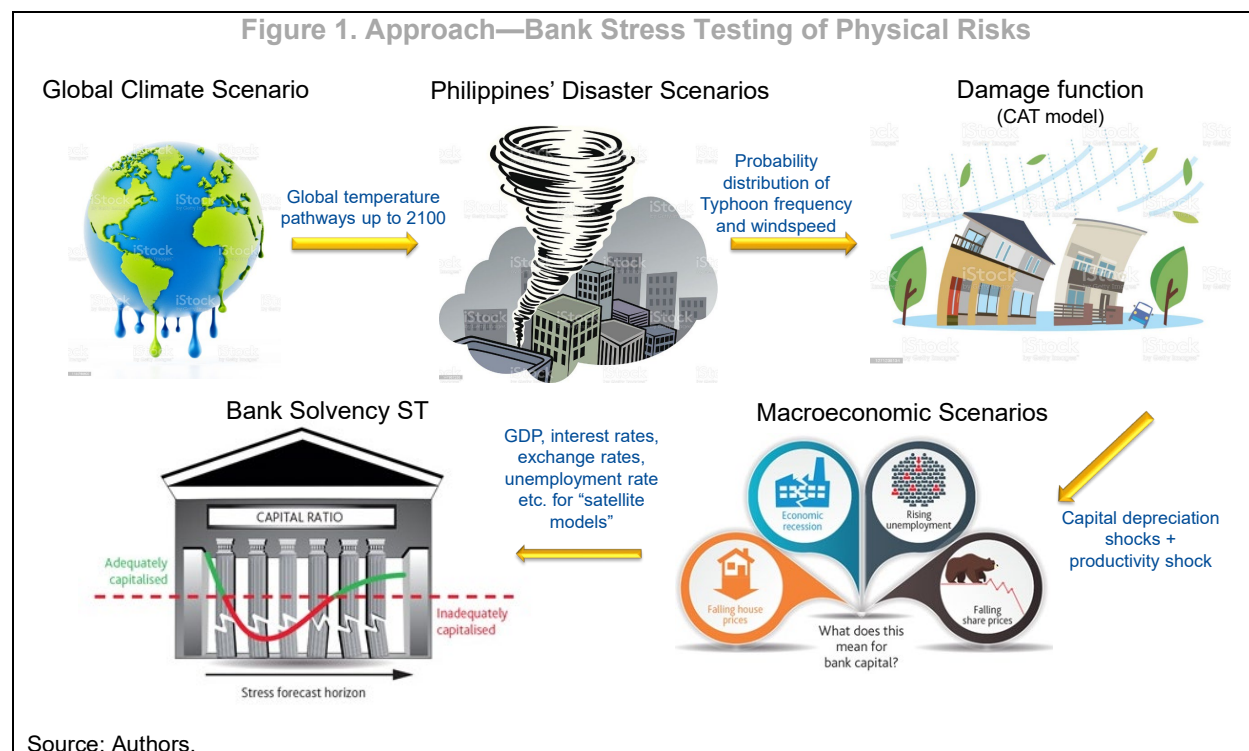
³ The country lies in the world's most typhoon-prone region. All major cities and most of the population reside on the coastline, including metropolitan Manila area that has about 60 percent of the country's economic activity. The 2019 Inform Global Risk Index ranks the Philippines as the most susceptible country to climate-change-related hazards. Similarly, the Global Climate Risk Index 2019 ranks it as the fifth most vulnerable to the physical risk.

⁴ RCPs are reported in IPCC's fifth assessment report (IPCC AR5 2013 and 2014). IPCC undertakes a periodic, systematic review of all relevant published research work on human-caused climate change.

⁵ In the insurance industry, these figures are called return period (the inverse of frequency or annual probability), indicating the average period until the next similar disaster occurs or probability of certain disaster occurring in the next year. Losses with a return period of 100 years (i.e., Value-at-Risk, VaR, at 99 percent) is often used for pricing disaster insurance. Losses with two hundred years (i.e., VaR at 99.5 percent) could be used for technical reserve adequacy, and 500 years (i.e., VaR at 99.8 percent) could be used for examining the risks to the reserves.

⁶ The climate module describes climate change in response to greenhouse gas emissions and its stock in the atmosphere. The impacts module—damage function—expresses physical and environmental outcomes as a function of climate variables. The economy module describes how emissions vary with growth and climate policies and how physical and environmental changes might affect a part of or the whole economy. This module could be modeled as: (1) equilibrium models such as DSGE models; (2) models with a richer cross-industry setup such as a computable general equilibrium model (CGM); (3) partial equilibrium models such as an energy system model that provides a detailed account of the energy sector; or (4) macro-econometric models such as NiGEM used for NGFS scenarios.

contrast, in this paper, the global climate scenario comes from the IPCC, and is based on full climate science models called global circulation models (GCMs).⁷ Then, we use the results of an existing study for the Philippines, developed by the Government of the Philippines and World Bank.⁸ The study derives changes in the Philippines-specific probability distribution of typhoons due to climate change by applying results from several well-known downscaled climate models (Gallo and others, 2018). Assuming exogenous global climate scenarios should be justifiable for a medium-sized economy like the Philippines, whose economic growth and energy policies have only a small impact on global greenhouse gas emissions.



We used a country-specific CAT model to project damages instead of an arbitrary one, as found in IAMs. CAT models produce the value of lost properties estimated in a bottom-up manner with micro-data, in contrast with arbitrary damage functions used in IAMs. CAT models were originally developed for managing tail property insurance risks (Lloyds 2014). They are based on the science and engineering studies of natural hazards and their impacts on specific assets like buildings and infrastructure. Most CAT models first simulate numerous hazard events (for example, all potential typhoons or floods that could impact a region), then incorporate the exposure data and vulnerability functions for properties and estimate the damage (lost property values) for each generated hazard. The output is a probabilistic set of risk statistics at property levels, such as recovery values. These estimates are combined with additional information, such as concentrations of risks and correlations of damage across the region, to produce probability distributions of potential economy-wide physical capital losses. Their simulation-based approach is particularly suited to estimate catastrophic losses from tail events where historical data are scarce or non-existent, (for example, once in 100 years and -above

⁷ GCMs are substantially more complex than economic models. A typical GCM contains codes to fill 18,000 pages of printed text, the input of hundreds of scientists over many years to build and improve, and a supercomputer as large as a tennis court to run.

⁸ Developed by the World Bank's Disaster Risk Financing and Insurance Programme (DRFIP) in collaboration with the government of the Philippines and supported with funding from the United Kingdom government.

events are usually not accurately documented in the recorded history). Moreover, we used unique Philippines' data showing physical capital's locations and their vulnerability to typhoons, rather than a more generic approach to proxy such data with GDP—the approach used for NGFS scenarios.

Another unique feature of this paper is that we coupled the CAT model and climate model to generate scenarios to project future damages from disasters for bank stress tests. Typical CAT models use current climate parameters, since they are used to price and manage risks from property insurance values, which usually have a short (one year) contract period. To consider potential future losses, one needs to replace the current climate parameters with those for the future, ideally drawing on country-specific projections from climate models. Coupling climate and CAT models has become more common in the insurance industry in recent years.⁹ Nonetheless, this was the first application to bank stress testing that the authors are aware of. Using the approach laid out in Ranger and Niehorster (2012), we modified the hazard simulation parameters within the CAT model based on the combination of GCM and Regional Climate Model (RCM) outputs (Gallo and others 2018) to obtain risk statistics for future scenarios suited for the Philippines.

The results indicate that extremely rare typhoons' impact on GDP growth could be systemic in the Philippines even now, and it would worsen substantially with climate change. Even under the current climate conditions, rare disasters with return periods of 100 years or above could reduce GDP by 3½–8½ percentage points at the peak. With climate change, these rare typhoons could reduce GDP by 5–14 percentage points—about 40–60 percent more than now. Such reduction of GDP is more than that observed during past financial crises, such as the Asian financial crisis and global financial crisis. However, the economic impact is relatively small for typhoons that could occur once in 25 years or less—a tail level relevant for standard bank stress tests. The increase of economic impact from chronic typhoons appears small per year, reducing the annual GDP growth rate by 0.12 percentage points. But it is also worth noting that the cumulative impact of chronic typhoons is more than the impact of severe but rare ones. The cumulative effects of chronic typhoon damage on GDP over 43 years reach a 5.2 percent—equivalent to the peak GDP impact of a once-in-100-year typhoon.

Nonetheless, bank stress tests indicate that the impact of climate change on typhoons alone may not reduce bank capital to worrisome levels unless compounded with other disasters. Without compounding events, climate change in the future would reduce bank capital ratios visibly only in the tail events of once in 500 years. Still, the decline is small at one percentage point. Also, the difference of capital ratios between baseline and a 500-year return period typhoon remains minimal—a maximum of 0.2 percentage points in the current scenario and 0.9 percentage points in the future scenario. These benign results partly reflect the Philippines' healthy macro-financial conditions at the start of the stress (end-2019). The country had a fairly healthy banking system, strong economic growth, and limited economic and external vulnerabilities. The impact of chronic typhoons is also tiny: even though they have a much larger cumulative impact on GDP than extreme events over the long run, banks also have additional buffers from cumulative long-term profits to absorb shocks. However, the compound risk of an extreme typhoon and a COVID-like pandemic significantly reduces bank capital. In future scenarios, a joint shock increases the impact of typhoons on bank capital by 2.2 and nearly 8½ percentage points for 25- and 500-year return period events, respectively, compared with the baseline. The message is in line with Monasterolo, Billio, and Battiston (2021) and Dunz and others (2021) that emphasized the importance of compounding climate risks with COVID, which could amplify the overall effects due to non-linearly.

⁹ Property insurance contracts are usually annual. If insurers observe changes in hazard risks, they can adjust insurance premiums quickly, limiting incentives to consider long-term climate change effects. However, recent changes in regulatory requirements have led to a change in practice (Golnaraghi and others 2021).

Our results appear to be broadly comparable to the estimates under the 2021 NGFS scenarios where projections from both approaches are available. Both scenarios show that future damage rates for once-in-a-100-year typhoons increase about 30–40 percent under RCP 8.5, and the corresponding GDP impacts are about 5 percent. This finding is good news for both our and NGFS approaches, indicating the robustness and complementarity of the two different analytical strategies in this specific case and common return periods and projection horizon.

At the same time, our approach can provide richer information on tail events than the NGFS scenarios, even though it requires substantial country-specific data and climate model analyses. The NGFS scenarios offer estimates under various global emissions scenarios—not just RCP 8.5 as used in this simulation—but only for once-in-a-100-year disasters. In contrast, our scenarios provide detailed outcome across different return periods, incorporate uncertainties in the underlying climate models suited for the Philippines, and present more details of the macroeconomic and financial implications of the hazard under consideration.

These relatively benign stress test results should be interpreted with caution. Our exercise focuses on typhoon wind destruction alone and does not include other climate-change-related risks that could amplify impacts, such as flood and sea-level rise. Furthermore, the exercise focused only on macro-economic-level transmission channels of severe typhoons. Due to data limitations, it did not account for possibly concentrated effects from lower property collateral values and credit risk concentration. In the Philippines, bank loan data by industry and by some measure of location are available, but not by industry and location conjoined, constraining micro-level analysis such as that completed by the ECB (2021).

It is crucial to interpret the results cautiously, given the exceptionally severe nature of uncertainty with financial and economic analyses of climate change. These analyses face severe uncertainties at all layers, including (i) uncertainties with the link between socio-economic activities and greenhouse gas emissions; (ii) uncertainties in climate science studies that measure quantitative impact of emissions on global warming, and the impact of global warming on local climate-related phenomena such as typhoons and sea-levels; and (iii) uncertainties about the effects of the local climate-related phenomenon on the environment and social and economic systems, and their implication on financial stability. Additionally, there are complicating and not yet well understood feedback relationships among these dynamics.

The paper is structured as follows: Sections II, III, and IV discuss each of the three modules to establish climate risk scenarios—climate, disaster, and macro modules—and Section V focuses on the bank stress testing module. Some of the technical details of these modules are explained in appendixes. Section VI explains the sensitivity of macro scenarios to various NGFS scenarios of typhoons in the Philippines, showing the damage rate of impacted capital from once-in-100-year events for the mid-21st century and toward the end of the century. Section VII concludes.

Climate Scenario

We relied on the 2018 study by the Philippines Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA) for climate scenarios. The study provides the current probability distribution of storm frequency, intensity, seasonality, and spatial density and the projected changes for the Philippines for the mid-century years (2036–65) for a variety of GCM and RCM combinations. The study first selected a sub-set of

GCMs relevant to the Philippines from about 40 well-known models,¹⁰ based on whether a GCM produces a set of climate variables necessary to simulate typhoons in the Philippines and on best practice criteria established in the literature. Representing this broad range of climate scenarios is critical given the high level of uncertainty in future climate projections. Since GCM projection is usually too coarse (that is, 100–300 km horizontal grid) to consider typhoons in a specific country, researchers need to use RCMs to downscale the projection to higher resolution levels. The study selected three RCMs at 12–25 km resolution levels suited to model typhoons in the western North Pacific to represent the range of uncertainties in national-level climate projections. It confirmed their historical performance by comparing the simulation results with actual observation during 1971–2005 period.

As documented in Gallo and others (2018), the study assumes the high-emission scenario, RCP 8.5, from IPCC. The scenario increases physical risks, the most among all RCPs in IPCC's Assessment Report 5 (AR5, IPCC 2013 and 2014). It was the “business as usual” scenario when AR5 was drafted, leading to global temperatures by 2100 of 4.0–6.1°C above pre-industrial levels. While recent studies suggest that current climate policies could put us on a more optimistic pathway (UNEP 2020), especially beyond 2050, the RCP 8.5 was considered appropriate for a stress testing context to provide a worst-case scenario of future typhoon risk. Moreover, RCP 8.5 shows a similar impact to other RCPs up to 2050, which is the focus of PAGASA's study. This is because, due to hysteresis in the climate system, climate outcomes of different emissions scenarios do not significantly diverge before mid-century. Global temperature increases by 1.4 to 2.6 °C by the mid-21st century, which is lower than the end-21st century temperature projection of the same scenario (2.7–3.1 °C, CAT, 2021).

The study suggested that future overall typhoon frequency is likely to decline, but the relative number of intense typhoons in the Philippines could rise (Figure 2).¹¹ Out of five simulations (combination of GCM and RCM), three models suggest significant decreases in tropical cyclone frequency (two suggest little change). Four of the models agree on a projected increase in tropical cyclone “intensity”—measured by the maximum sustained wind speed—overall, with two showing significant increases. In all scenarios, year-to-year variability will remain high. This result is consistent with IPCC's findings for the western North Pacific (Seneviratne and others 2021) as well as Knutson and others (2020), referenced in the 2021 BOE exercise. The different results given by different models reflects the uncertainties in current understanding of how global temperature increases translate into local changes in extreme weather as described by the IPCC.

¹⁰ Various research institutions produce GCMs. Climate scientists conduct cross-model comparison exercises, called the [Coupled Model Intercomparison Project](#) (CMIP) once every five years or so, using the same data and key simulation parameters. The study reviewed 40 GCMs from the fifth round of CMIP, concluded in 2014.

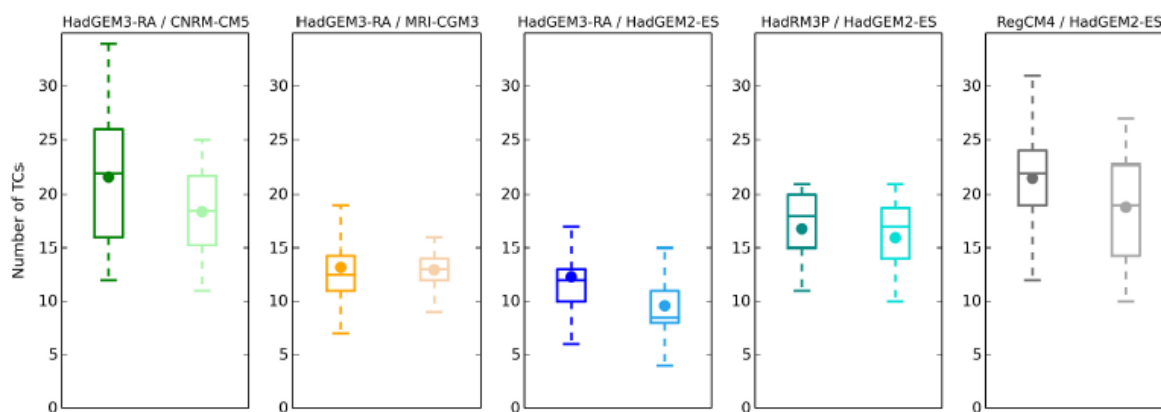
¹¹ The equivalent of category four and five hurricanes on the Saffir-Simpson scale used in the United States.

Figure 2. Climate Change's Impact on Typhoon Characteristics in the Philippines under RCP 8.5^{1/}

Most models predict that the frequency of typhoons is likely to decline in the future in the Philippines.

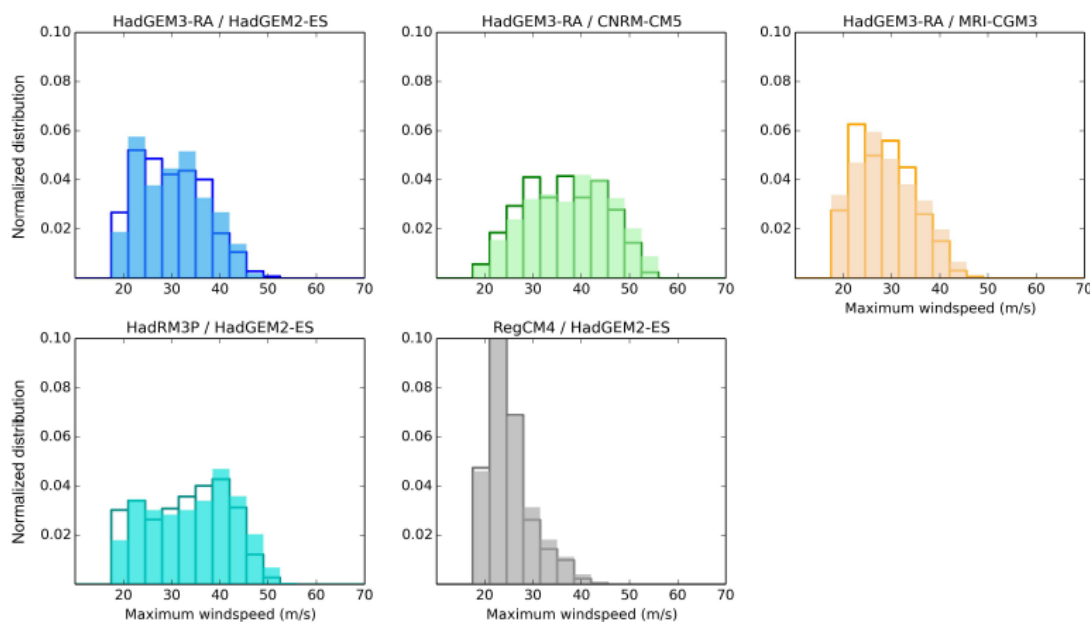
Panel 1: Annual tropical cyclone (TC) frequencies produced by the five climate models.

Historical (1971-2005) period (left) and future (2036-65) period (right) for the five climate models. The box limits correspond to the 25th-75th percentile, and the whiskers describe the range of values. The middle line of the box shows the median, and the circle indicates the mean of the simulation results.



These models produce significantly different intensity distributions with small increases of means, except for two models (HadGEM3-RA/CNRM-CM5 and HadRM3P/HadGEM2-ES), which project a significant increase.

Panel 2: Distribution of maximum intensities measured by maximum sustained wind speeds of tropical cyclones. Model-produced historical (1971-2005) period (lines) and future (2036-65) period (full colored bars)



Source: Figures 8 and 9 from Gallo and others (2018), which documents the details of the 2018 PAGASA exercise.

1/ The exercise used three global climate models HadGEM2-ES (developed by the UK Met Office Hadley Centre), CNRM-CM5 (developed by the Centre National de Recherches Météorologiques (CNRM) in France), and MRI-CHCM3 (developed by the Meteorological Research Institute (MRI), in Japan). HadGEM3-RA, HadRM3P, and RegCM4 are downscaling models to provide Philippines-specific projections based on the global climate models.

Disaster Scenarios

CAT models were originally developed to facilitate managing tail risks from extreme disasters for property insurers (Lloyd's 2014). Standard actuarial techniques based on expected mean losses are not appropriate to estimate catastrophe losses because historical loss data are scarce, especially for low-frequency (once in 100 years and beyond) high-impact events that could threaten insurers' solvency. CAT models combine science, engineering, economics, and finance to produce probability distributions of potential losses to a particular asset or locale from certain hazards. Since property insurance contracts are usually annual, typical CAT models only consider current hazards' likelihood and characteristics and ignore the effects of long-term climate change.

Most CAT models adopt a modular approach with the following four modules:

- The *hazard module* simulates numerous hazard events (for example, hurricanes or floods) based on the scientific models. Since property insurance is usually contracted annually, typical CAT models assume present-day climate conditions and do not account for climate change. The module typically produces an "event set" with indicators such as typhoon intensity (wind speed) and trajectories pertinent to their impact for typhoons.
- The *exposure module* requires individual property data, with their location, value, building materials, floors, and design standards. For property insurers, exposures usually represent the location and qualities of the properties covered by their contracts.
- The *vulnerability module* uses engineering damage curves specific to the type and characteristics of properties and infrastructures to estimate the damages from the exposure to each generated hazard event.
- The *financial module* calculates loss statistics using actuarial techniques. The most commonly used financial outputs are the Annual Average Loss (AAL) and the Exceedance Probability (EP) curve (a graph showing the probability that a certain level of losses will be exceeded).

We used the CAT model developed by the World Bank and the government of the Philippines coupled with climate scenarios based on Gallo and others (2018).¹² The hazard module generated ten thousand simulated events based upon detailed historical catalogs of typhoons to represent the range of potential future events. For future scenarios, the parameters employed to simulate typhoons were recalibrated to represent future climate conditions based on Gallo and others (2018), following the approach outlined in Ranger and Niehörster (2012). The simulated events are used to calculate the geographic distribution of typhoon intensity (wind speed).

The outputs of the hazard module model were then overlaid on unique country-specific exposure data and detailed damage functions used by insurers to estimate losses. The exposure data show public and private assets at risk. Private assets include residential, commercial, and industrial buildings. Public assets include

¹² The model was developed as a part of the recent World Bank's Disaster Risk, Financing, and Insurance Program for the government of the Philippines with technical support from Air Worldwide—one of the three globally well-known vendors for CAT models (Lloyds 2014) used by insurers. The same group from the World Bank contributed substantially to creating the 2021 phase II NGFS physical risk scenarios.

airports, ports, hospitals and clinics, power plants, prisons, government buildings, schools and universities, rail infrastructure, roads, and bridges. The database was assembled using various sources, including from official agencies in the Philippines. Such data are significantly more detailed than the data previously used for climate financial risk assessment, for example, in the gridded GDP-based approach adopted by the NGFS. The vulnerability data draw upon detailed insurance industry damage functions for different building types, adapted for the Philippines using local data. While the damage rate could decline in the future with mitigation and adaptation policies and the quality of infrastructure improves, we did not incorporate this channel in our scenario.

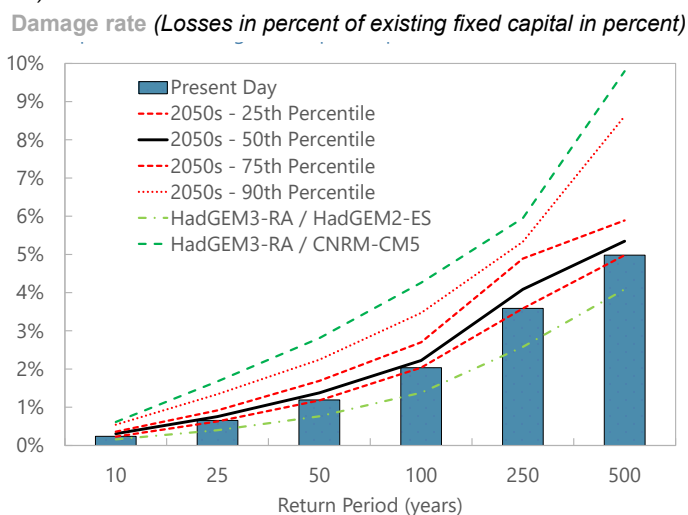
The simulation-based CAT model output includes disasters that have never been recorded in recent history for both current and future scenarios. Damages from typhoons increase with wind speed, but they also depend critically on trajectories. Even for a record typhoon by wind speed, physical capital losses could be moderate if it passes through rural areas (though human cost could be substantial). Indeed, most typhoons land in rural parts of the Philippines. For example, the Super Typhoon Yolanda (called Haiyan in the region) in 2013 produced the world record highest wind speeds measured at landfall of 315 km or 195 miles per hour. She turned out to be the deadliest typhoon ever to hit the Philippines. Yet, the damage to physical capital was comparable to a roughly once-in-30-year event because its track passed through less developed areas. On the other hand, if major typhoons landed on metropolitan Manila, where nearly two-thirds of the country's economic activities are concentrated, the damage would be catastrophic. Manila has never experienced such damage before in recorded history but is exposed to such events. Therefore, it is relevant to consider such tail events in bank stress tests.

The simulation results indicate that damage rates for capital rise for rarer events under both future and current scenarios (Figure 3). Figure 3, panel 1 shows the distribution of estimated damage for private sector assets in the Philippines from all the 50,000 simulated typhoons (10,000 each for climate parameters from the five RCM outputs shown in Figure 2). Depending on its track, spatial extension and intensity at landfall, each typhoon causes different levels of losses. Even if they are very intense, if they pass rural areas—as most typhoons actually do in the Philippines—where buildings and infrastructure are sparse, the damage would be limited. On the other hand, if they pass metropolitan Manila area where capital stock concentrates, it could cause substantial damages even though the likelihood of such event is small. Each line shows damages of a given percentile across all the simulation results over different return periods. The vertical range reflects both the risk (uncertainty over the outcome for a given climate model) and model uncertainty over the five climate models for a given return period.¹³ The non-linear relationship between wind speed and damages increases damages non-linearly over the return period for most climate scenarios, both in medium (once in 50 years) and tail (once in 250 years) likelihood events. This non-linearity pushes up the damage rate (share of destroyed capital over stock) for rarer typhoons (panel 2 of Figure 3).

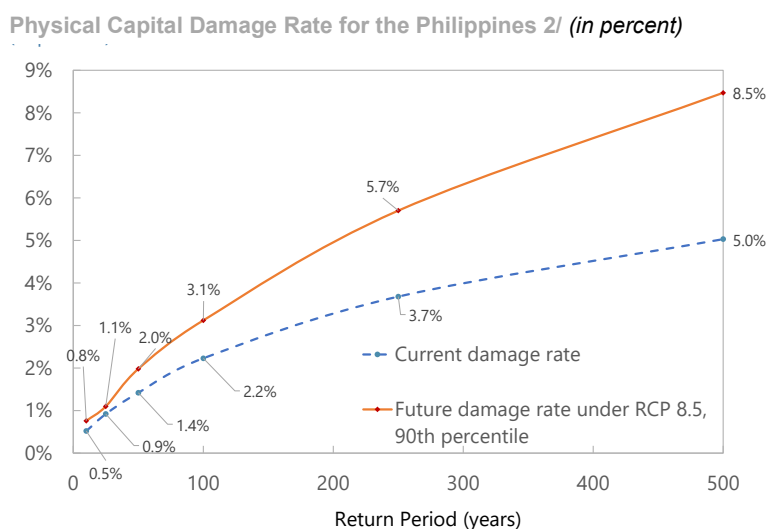
¹³ As discussed by Hansen (2021), financial and economic analyses of climate change face three types of uncertainties: (i) risk, which is about unknown outcomes from known probabilities and typically included in stochastic economic and financial models; (ii) ambiguity or deep uncertainty where one cannot even assign subjective probability over possible outcomes, and (iii) model misspecification indicating unknown ways in which a model might give flawed probabilistic predictions.

Figure 3. Estimated Physical Capital Losses¹

Panel 1: The model output shows wide ranges of potential losses, especially for tail events with longer return periods. For each return period, the future median losses are higher than current median losses, corresponding to about 25 percentile losses in the future scenarios. Moreover, losses rise non-linearly for rarer events for any given level of losses (a specific percentile line).



Panel 2: As a result, the damage rate (the share of the value of lost physical capital over the value of the existing stock) increases for rarer events. For once-in-500-year events, the future damage rate is about 70 percent higher than the current damage rate, while for once-in-100-year events, the damage rate increases by 40 percent.



Source: Authors.

1/ The top chart covers private-sector assets only, but the exercise has separate estimates for public assets as well.

2/ Destroyed capital stock in percent of existing stock.

Importantly, Figure 3 shows that the Philippines' physical capital damage from typhoons is likely to increase in the future owing to climate change under the RCP 8.5 scenario. Gallo and others (2018) show that, while the total number of typhoons hitting the Philippines declines, there could be more intense typhoons. It indicates a wide range of potential losses, especially for tail events with longer return periods, for example, going up to about 8½ percent from 5 percent in once-in-500-year events in the mid-21st century. For each return period, the future median losses are higher than current median losses (equal to about 25 percentile losses in the future scenarios), indicating that damage is likely to increase in the future scenario. We used the higher estimated losses (90th percentile) for the rest of the analysis to make the exercise conservative (that is, severer), consistent with best practice in systemic bank stress tests.

On the other hand, the average annual damage rate, which indicates chronic impact, appears small per year both now and in the future. The current annual average damage rate of capital is about a quarter percentage point, which could increase to a third percentage point under the RCP 8.5 scenario in the mid-21st century. This is much smaller than the acute damage rate for relatively moderate tail events when they occur—about three percentage points for once-in-100-year events. Of course, cumulative effects of chronic damage (for example, 31 percent over 100 years) are substantially more extensive than the single-year destruction of rare events (3.1 percent for a once-in-a-100-year event).

Macro Scenarios

Whether a disaster becomes a systemic (economy-wide) macro-financial shock depends not only on the characteristics of the disaster but also on the size and diversification of an economy. For small economies, one intense hurricane can have a devastating impact. For example, a Central American study found that a one standard deviation increase in a hurricane's intensity leads to a decrease in total per capita GDP growth of 0.9–1.6 percent and a 3 percent decrease in total income (Ishizawa and Miranda 2016). Also, the literature suggests that reconstruction after major disasters can last five to 10 years, magnifying the impacts of the shock on total GDP and consumption. However, the macro-level impact could be small for large and diversified economies by geography and industries, as was hurricane Katrina in the US in 2005. Despite its enormous direct damage, Katrina was not a systemic macroeconomic event for the United States. Indeed, the Federal Reserve Board continued to tighten monetary policy throughout 2005 and 2006 in response to inflationary pressures and overall robust macroeconomic growth. Therefore, most of the studies on the impact of Katrina have focused on the local economy and displaced population (see, for instance, Vigdor 2008, Groen and Polivka 2008, and Deryugina, Kawano, and Levitt, 2018). Even in these studies, they found that the impact on a significant number of the displaced population (about 400,000) regarding employment and income was small and transitory.

Therefore, one would need an adequate macro-financial model to translate damage from physical risks to economic outcomes.¹⁴ The Philippines is much more geographically and economically diverse than island countries but also much smaller than the United States. Accordingly, without a model-based analysis, the extent to which disasters could cause systemic economic impact remains unclear. In doing so, we took a standard New Keynesian DSGE model with Taylor Rule and double financial accelerator (corporate and

¹⁴ An alternative to this macroeconomic approach is a micro-level bottom-up approach. The impact is likely to be different depending on the location and industry. One could, in principle, consider industry-by-industry impact and then aggregate them up. For example, the impact on the agricultural output could be estimated by a crop-yield hazard model instead of a CAT model (see Nelson and others 2014). However, such a bottom-up exercise is very resource intensive.

banking sector). We interpreted typhoons' destruction of physical capital as a one-time capital depreciation shock using the damage rates from disaster scenarios. To be precise, the damage estimated with the CAT risk model covers buildings and infrastructure, and not all the capital used for production (such as manufacturing machinery and computers). However, the damage rate is applied to all the capital stock as an approximation, assuming that other capital is geographically distributed in the same way as buildings and infrastructures.

To fully account for the macroeconomic impact of extreme typhoons, it is essential to include the channels that cause potentially long-lasting amplification effects. Our model incorporates the following two channels:

- Long-lasting decline in total factor productivity (TFP). The disaster does not only reduce the stock of capital, but it also creates a misallocation of the remaining capital, leading to a decline in TFP (Hallegatte and Vogt-Schilb, 2019). In particular, the loss of infrastructure will reduce the productivity of other (non-affected) assets in the rest of the economy (Hallegatte and others 2022). The “stock” of roads decline after a disaster, but the roads that remain usable may not be the most important in the transport system. Compared with an optimal distribution of the remaining capital, and because it's impossible to “reallocate” roads to their most productive use, the capacity of the transport system may decline more than what is suggested by the asset losses, i.e., the productivity of the road system will decline, with implications on the productivity of all other business and assets.¹⁵ Similarly, the still inhabitable buildings are not necessarily the ones hosting the most critical businesses or activities. It is possible to reallocate a large share of capital over the medium term through investment and relocation (for instance, the most productive firms will move to inhabitable buildings), but it takes time and is costly. The result is a drop in TFP, in addition to the decrease in capital stock. Empirical studies confirm that disasters reduce the stock of capital and TFP (Bakkensen and Barrage 2018 and Dieppe and others 2020). Roughly one-third of the impact on GDP stems from capital destruction, and the other two-thirds are due to the accompanying TFP shock.
- Time for reconstruction. Incorporating time for reconstruction into a model is also critical. In a simple model with no financial and technical constraints on the reconstruction, damages can be repaired in a few weeks or months. In reality, reconstruction takes much longer for financial, regulatory, and technical reasons:
 - a. *Financial.* In many countries, the reconstruction of local infrastructure is paid for by the government but done by local authorities. However, budgetary processes can take months to transfer the resources from the central government to the local authorities, slowing down reconstruction. And private actors—firms and households—may be unable to mobilize enough resources to rebuild at once and often decide to repair homes and factories in phases, spreading the cost over the years.
 - b. *Regulatory.* After a large shock, reconstruction requires long-term planning, particularly if the goal is to “build back better.” For instance, it may be decided not to rebuild in the most at-risk areas. But doing so requires a political process that can take several months. And in the absence of pre-approved contracts and specific public financial management arrangements, procurement can also delay reconstruction by months or more.

¹⁵ As an example, the damages to the Bay Bridge in the San Francisco Area in 1989 had an impact on the Bay Area transport system and capacity that is much higher than what the same amount of damages would have caused if they affected secondary roads only.

c. *Technical.* Reconstruction increases demand in specific sectors that have capacity constraints. For instance, debris removal after a hurricane can take a long time because heavy equipment is lacking. Or specific skill providers may be absent, like roofers or carpenters. The constraints in some sectors can slow down reconstruction significantly and is visible in wages and prices in the construction sector (something referred to as a “demand surge” in the literature and the insurance industry).

It is also vital to consider the economic impact of moderate but more frequent disasters and how it might evolve due to climate change. As discussed earlier, the annual average damage rate of moderate but chronic typhoons rises in the future scenario. This means a higher steady-state capital depreciation rate and, therefore, growth rate in the future cumulatively in the long run. At the same time, chronic typhoons may not bring about as strong an amplifying TFP impact and time-to-reconstruct effects as acute disasters, limiting the marginal impact on GDP for a given physical capital damage rate.

Against this backdrop, our New Keynesian DSGE model, described in detail in Appendix 1, incorporates these three channels:¹⁶

- *Immediate physical destruction.* Immediate losses of assets and capital are expressed as a shock $z_{d,t}$ to the depreciation rate of capital in the model $\frac{\delta}{z_{d,t}}$. A decline in $z_{d,t}$ raises depreciation. The shock size was calibrated such that depreciation increases identical in magnitude to the damage rates drawn from the disaster scenarios.
- *Long-lasting decline in total factor productivity.* TFP decreases in parallel to the increase in the depreciation rate. The Cobb-Douglas GDP production function is $y_t = z_{y,t} k_{t-1}^\alpha n_t^{1-\alpha}$, where k and n are capital and labor inputs respectively and $z_{y,t}$ is TFP shock in period t . The shock $z_{y,t}$ was calibrated to decline in magnitude twice as much as the increase in depreciation. So, if depreciation increased from 2.5 to 6.5 percent—e.g., by four percentage points— $z_{y,t}$ would fall from 1 to 0.92.
- *Time for reconstruction.* The model incorporates habits in consumption and investment adjustment cost, such that it takes time for households to adjust their consumption, and time for firms to adjust their investment plans. In addition, the shock to the depreciation rate $z_{d,t}$ is short-lived, while the TFP-shock $z_{y,t}$ has long persistence (assuming that the allocation of capital and TFP eventually gets back to its pre-disaster level).

As for public policies, while the model includes standard monetary and fiscal policies, it does not incorporate any climate- or disaster-specific policies, which could mitigate the impact. The monetary policy follows a standard Taylor rule, and tax revenue is used for fiscal spending. In reality, upon major disasters, the Philippines received a considerable amount of international aid, post-disaster financing, and pre-arranged contingent financing programs from international financial institutions, and increased remittance inflows from Philippine workers overseas upon major disasters. Also, if underdeveloped property and disaster insurance and

¹⁶ We also considered a real business cycle (RBC) model with standard (non-Philippines specific) parameter assumptions and incorporated the same three channels. The results (the magnitude of disaster impact on GDP) were broadly the same, suggesting that the shocks applied yield the same GDP response for various DSGE models. While the New Keynesian and the RBC DSGEs yield similar results in terms of GDP response, we prefer the New Keynesian model as it was estimated with macro and financial variables of the Philippines.

re-insurance markets grow in the future, insurance payouts could ease financial constraints and shorten reconstruction time. They could also limit the loss of property collateral values for bank loans and, therefore, loss-given-default (LGD). However, we do not include these channels, given the uncertainty over the potential market development in the future.

The results indicate that extremely rare typhoons' impact on GDP growth could be systemic in the Philippines even now, and it would worsen substantially with climate change (Table 1). As shown in Table 1, even under the current climate conditions, rare disasters with return periods of 100 years or more could reduce GDP by 3½–8½ percentage points at the peak. The impact is comparable to or greater than the impact of the global and Asian financial crises for the Philippines (about 3–5½ percentage points) and the IMF's estimate of the economy's potential growth at 6½ percent per year (IMF 2021). It is also comparable to one to two standard deviations of the annual GDP growth rate of 3½–6½ percentage points, which is often used to determine the shock size in FSAP bank stress tests.¹⁷ With climate change, rare typhoons with return periods of 100 years or more could reduce GDP by 5–14 percentage points—about 40–60 percent more than the impact under current climate conditions. Such reduction of GDP is more than those observed during the past financial crises and, therefore, systemic (i.e., an aggregate shock). For one-in-a-500-year typhoons, the GDP impact is comparable to that observed during the COVID crisis.

Nonetheless, the economic impact is relatively small for typhoons that could occur once in 25 years or less—a tail level relevant for systemic bank stress tests. Twenty-five years is comparable to the length of the financial cycle presumed (20–25 years) to calculate frequently used credit gap estimated by the Bank for International Settlements (BIS). If the trough of the cycle is considered as a systemic financial sector distress event, then the estimate suggests a systemic bank stress could happen once in 20–25 years. IMF-WB FSAP stress tests usually benchmark the size of GDP stress to the level observed once in 20 years, too.

The impact of climate change on GDP declines caused by rare typhoons generally seems higher for rarer events. Climate change increases the future impact on GDP by 20 percent for once-in-25-year typhoons compared with the impact under the current scenario. The increases are higher for events with a once-in-a-50-year frequency or rarer, reaching 60 percent for once-in-500-year events. This change in GDP impact seems roughly proportional to the deterioration of damage rates between current and future events. Across various return periods, a one percentage point increase in damage rate deepens peak GDP declines by 1½ percentage points (calculated as columns G over C in Table 1).

On the other hand, the chronic impact of climate change appears relatively small per year. The impact, measured by the reduction of annual average GDP growth rate in a steady state, is -0.12 percentage points per year. This appears relatively small, especially compared with the strong potential growth rate of 6½ percent of the Philippines. This seems to be driven by various non-linear amplification mechanisms in our macroeconomic model (especially the accompanying TFP shock and time to reconstruct). The impact on GDP relative to physical capital damage rate is smaller than extreme typhoons. A one percentage point increase in chronic damage rate means a 0.4 percentage point increase in GDP impact (columns F over B in Table 1, chronic disaster row), in contrast with a 1½ percentage point increase for extreme events.

¹⁷ Using GDP data for 1980–2019. A two-standard deviation shock proxies once-in-20-year economic shock. IMF-WB FSAP stress tests usually benchmark the size of stress to a two-standard deviation shock to keep shock severity comparable across jurisdictions.

Table 1. Disasters' Impact on Capital and GDP for the Philippines

(In percent unless otherwise indicated)

Return period (years)	Physical capital: Damage rate				GDP: Peak level decline			
	Current	Future	Effects of climate change		Current	Future	Effects of climate change	
	A	B	C = B-A in % pts.	D=C/A in %	E	F	G = F-E in % pts	H=G/E in %
10	0.52	0.76	0.24	46	-0.86	-1.25	-0.4	46
25	0.92	1.10	0.18	20	-1.52	-1.82	-0.3	20
50	1.42	1.98	0.56	39	-2.34	-3.27	-0.9	39
100	2.23	3.12	0.89	40	-3.68	-5.15	-1.5	40
250	3.68	5.70	2.2	55	-6.07	-9.41	-3.3	55
500	5.03	8.47	3.44	68	-8.65	-14.00	-5.4	62
Chronic	0.23	0.31			...	-0.12 ¹
Memo items: Actual peak GDP shock in the past crises ²								
GFC			-2.90	...		
AFC			-5.69	...		
COVID ³			-14.49	...		
1980s ⁴			-16.50	...		

Source: Authors and IMF World Economic Outlook (WEO) database.

Notes: GFC = global financial crisis; AFC = Asian financial crisis

1/Steady-state GDP growth rate difference from current scenario.

2/ For the past crisis, the difference of real GDP growth rate between the crisis-year and the year before. Only for the political turmoil episode in the mid-1980s, the figure shows the 1983 growth rate minus the 1984 and 1985 growth rate since the country experienced two consecutive years of -7.3 percent contraction.

3/ Based on IMF October 2020 WEO.

4/ The political-turmoil-related crisis in 1984–85.

Having said that, the chronic impact of climate change could significantly reduce GDP and, therefore, bank profits cumulatively over decades. Under the RCP 8.5 climate scenario, cumulative effects of chronic typhoon damage on GDP over 43 years reach 5.2 percent—equivalent to the peak GDP impact of a once-in-100-year typhoon (column F in Table 1). So, overall, chronic disasters are more damaging to economic growth than extreme disasters over the long run. Nonetheless, their annual impact is small, and banks are likely to withstand them with their annual profit buffers. Therefore, chronic disasters are unlikely to cause systemic financial instability, namely, events that cause acute short-run losses to many or systemically important banks beyond their profits and thereby reduce capital.

Based on these results, we established 10 macro-financial scenarios for extreme typhoons taking baseline scenarios with and without compounding shocks and highlighting the effects of climate change (Figure 4). COVID-19 was used as an additional stressor in the scenarios to represent the potential for compounding shocks associated with climate change. For the current scenario, the baseline with COVID-19 is IMF's World Economic Outlook (WEO) forecast as of October 2020, and the baseline without pandemic is from January 2020 vintage. We assumed the same baseline economic paths for the future scenario as well. This implies economic growth momentum and drivers and macro-financial conditions at the start of stress in the future remain the same as 2020. While such an assumption may not be realistic, it helps to highlight the marginal effects of climate change alone in the assessment. There are four adverse scenarios for each baseline: once in

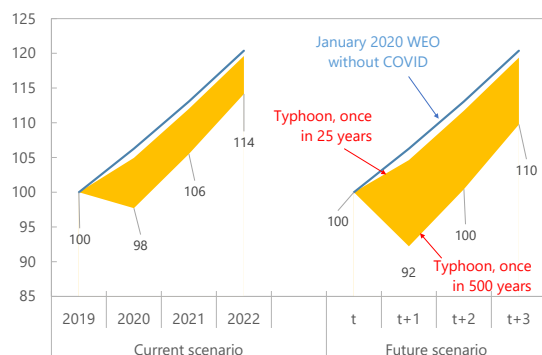
25- and 500-year typhoons using current and future disaster risks. As shown in Figure 4, the impact of a once in a 25-year typhoon is moderate across all four cases. The effects of climate change become more visible in tail typhoon events (once in 500 years).

The compounding shock scenario with a pandemic is substantially more severe than the one without. The Philippines' economy was one of the most severely affected by COVID-19. The GDP growth rate declined from about 6 percent in 2019 to -9½ percent in 2020—about a 15-percentage point reduction. The country undertook one of the tightest lockdown measures in the world upon the arrival of COVID, leading to exceptionally severe economic costs. The 15-percentage point reduction is similar to the GDP impact of once-in-a-500-year typhoon under the future scenario. This means that the total size of the compounding shock of an extreme typhoon and pandemic is close to double the historical worst observed during the political turmoil episodes in the mid-1980s.

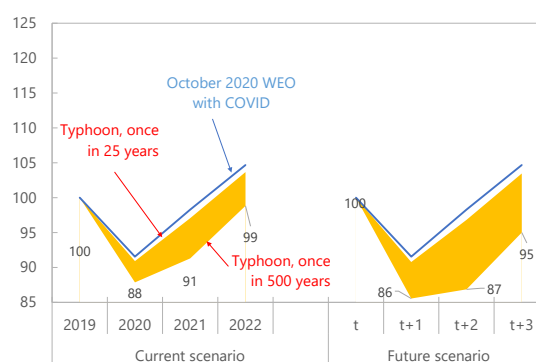
Our bank stress test does not examine scenarios with chronic disasters. While their long-term cumulative effects on economic growth are more than those stemming from extreme tail events, these could be absorbed by banks' profits. Bank stress tests for systemic risks usually focus only on acute losses in the short run that could reduce capital.

Figure 4. GDP Assumptions for Climate Change Stress Test
(Severe typhoon is assumed to hit the country in Q3 2020)

Macroeconomic Impact of Typhoons-Normal Time
(2019 real GDP = 100)



Macroeconomic Impact of Typhoons and Pandemic
(2019 real GDP = 100)



Sources: Authors and IMF WEO database.

Bank Stress Test

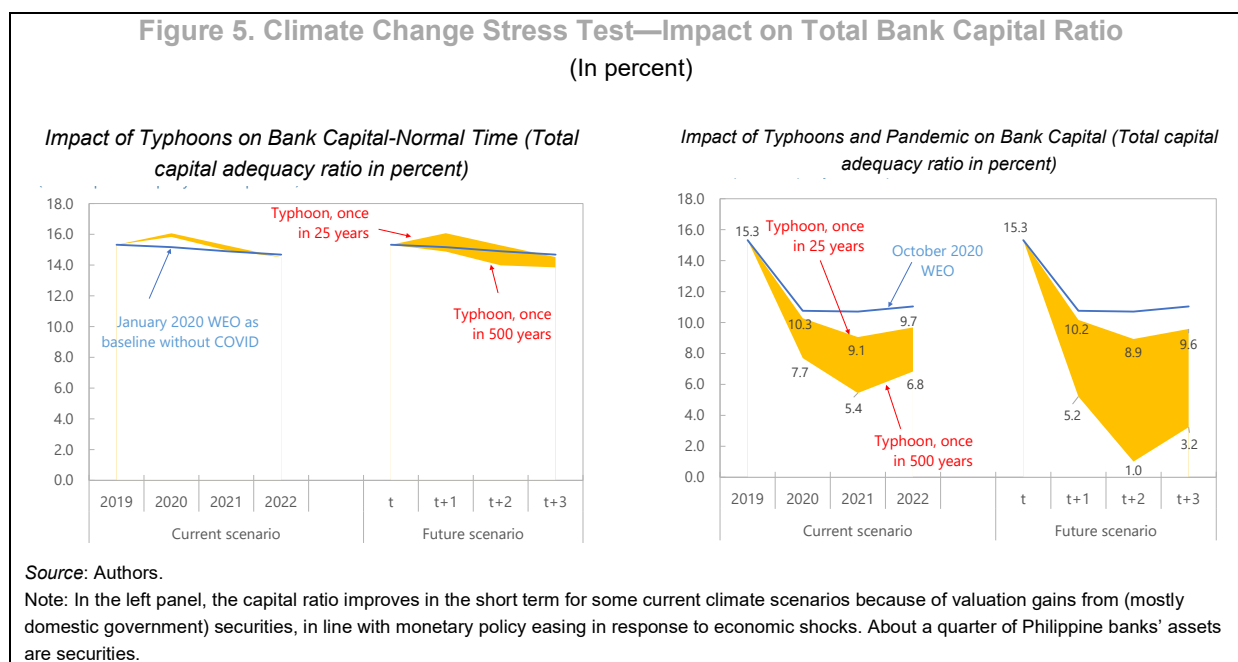
The solvency stress test of banks follows broadly the same standard FSAP method. It covers 46 universal and commercial banks in the Philippines, accounting for about 92 percent of the banking system by assets. Detailed bank-level financial statement data were provided by the bank supervisor and the central bank of the Philippines. The test includes credit and market risks (valuation losses from securities and the effects of exchange rate movement) and shocks on net interest income and pre-impairment income. Test horizon is three years after a disaster, one starting in 2020 and the other starting at some point in the mid-21st century. The bank balance sheet is assumed to grow at the same rate as nominal GDP, and the structure of assets and liability remains the same within the three-year stress testing horizon in both current and future scenarios.¹⁸ Banks can strengthen capital only through retained earnings after tax and dividend payments. Bank capital ratios are calculated following Basel III standardized approach adopted by the national regulator. Risk-weighted-assets (RWAs) evolve with credit growth net of increases in provisions. They are further adjusted by the new nonperforming loans (NPLs) that are not provisioned (to reach the weight of 150 percent required by the regulation). All satellite models are estimated by authors using the quarterly historical data of the Philippines for 2005–19. See Appendix II and IMF (forthcoming) for more details.

The test adopts a few simplifying assumptions to highlight the marginal impact of climate change keeping other things equal. In particular, bank business model, balance sheet structure, financial development (bank assets and credits in percent of GDP), macroeconomic structure, and economic growth are assumed to remain the same between now and mid-21st century. We assumed the same baseline economic paths for both current and future scenarios, implying economic growth momentum and drivers and macro-financial conditions at the start of stress in the future remain the same as 2020. End-2019 actual bank balance sheet data were used as the starting point of the tests for both current and future scenarios. Such assumptions may not be realistic for a dynamic emerging market economy like the Philippines. However, trying to incorporate forecasted macro-financial structures a few decades ahead masks the marginal contribution of climate change and introduces substantial model uncertainty. The focus of our work is not to correctly forecast the future. Rather, it is a stress test exercise that aims to identify potential impact of climate change under hypothetical conditions to identify the main vulnerabilities of the economic and financial systems to climate change risks.

Unlike for a typical stress test, we do not apply any hurdle rate to judge the pass or fail of banks and link the results with additional capital requirement discussion. Our analysis aims to examine the potential magnitude of stress to banks in the event of extreme disasters and climate change, not to estimate the additional capital requirements for climate change risks. Currently, the literature on financial stability risk analysis of climate change is still very young and subject to notable uncertainty. As a result, most central banks or regulators are not considering linking their climate risk analysis to capital charges in the near term, unlike standard supervisory (micro-prudential) stress tests (FSI 2021). Moreover, our macro scenarios show that the impact of typhoons could be systemic only for very rare events with the likelihood of below once in 100 years, or even further into the tail beyond what is typically considered in any macro- and micro-prudential stress testing of banks.

¹⁸ In other words, this paper assumes so-called quasi-static balance sheet assumption where bank assets and credit to GDP ratios remain constant.

The results show that the impact of climate change on typhoons alone may not cause extreme financial instability (Figure 5). Without compounding events, climate change in the future would reduce bank capital ratio visibly only in the tail events once in 500 years. Still, the decline is small at one percentage point. Indeed, bank capital could rise immediately after the shock. About 25 percent of bank assets are securities, primarily domestic sovereign bonds. Automatic policy rate cuts following the standard Taylor-type inflation targeting rule add valuation gains to the bank balance sheet, which, in the short run, dominates the effects of higher credit cost and other profitability shocks that emerge with longer lags.¹⁹ Also, the difference of capital ratios between baseline and a 500-year return period typhoon remains very minimal—a maximum of 0.2 percentage points in the current scenario and 0.9 percentage points in the future scenario.



These benign results partly reflect the Philippines' healthy macro-financial conditions at the start of the stress. We used end-2019 bank balance sheet data, the last quarter before COVID started. As discussed in IMF (2021a), the Philippines' banks had healthy capital and liquid buffers with strong credit quality (Annex III). At the end of 2019, the total capital ratio was about 15 percent with a non-performing ratio of two percent, and liquid-assets-to-total-assets ratio of 32 percent. Macroeconomic conditions were also strong, with a GDP growth rate of 6 percent and consumer price inflation of 2.5 percent (Annex IV). Vulnerability of public and external sectors was also well contained with a gross public debt ratio of 37 percent, external debt at 22 percent, and current account deficits of 0.9 percent. These figures put the Philippines as a fast-growing low vulnerability EMDE.

However, the possibility of compounding risks could drastically strain bank capital. Even without climate change, the compound risk of an extreme typhoon and COVID-like pandemic significantly increases the additional effects from typhoons for both once-in-a-25- and 500-year disasters. Comparing the results of the current climate conditions under normal time and pandemic baselines, a joint materialization of typhoons and

¹⁹ The short-run effects could be adverse if we consider an alternative macro-financial scenario where the country risk premium of the Philippines jumps enormously in response to the expected macroeconomic impact of extreme typhoons. Capital outflows could depress the exchange rate, boosting inflation through pass-through effects. The rate hike needed to keep inflation at about target causes valuation losses with bonds, dragging down bank capital.

pandemic increases the marginal impact of typhoons by two percentage points for a 25-year return period typhoon and 5½ percentage points for a 500-year return period typhoon. In future climate conditions, a joint typhoon and pandemic shock strengthens the additional impact of typhoons by 2.2 percentage points for a 25-year return period typhoon and nearly 8½ percentage points for a 500-year return period typhoon compared with the scenario without pandemic.

The finding is in line with other recent papers on compounding risk of climate change and pandemic. Monasterolo, Billio, and Battiston (2021) and Dunz and others (2021) emphasized the importance of compounding climate risks with COVID. Their models attempted to incorporate richer and complex climate and finance interactions than our approach, and conclude compounding risks are indeed important. While our paper relies on standard New Keynesian DSGE model with macro-financial linkages but without any specific climate-related interactions, Figure 5 replicate non-linear effects of compounding risks.

The joint shock also intensifies the effects of climate change for extremely intense typhoons. For 25-year return period events, the effects of climate change remain small (the difference of the impact of a 25-year return period event in the current and future scenarios). However, for 500-year return period events, the difference between current and future scenarios with the pandemic rise to 4½ percentage points compared with one percentage points difference under normal time baseline.

These relatively benign results should be interpreted with caution. The exercise focuses on typhoon wind destruction alone does not include other climate-change-related risks that could amplify the impacts, such as flood and sea-level rise. It excludes damages from physical risk other than infrastructure damages from typhoons due to storm-wind. Furthermore, the exercise focused only on macro-economic level transmission channels of severe typhoons. For example, due to data limitation, it did not account for the impact on bank solvency from lower property collateral values that increases LGD. It did not include potential amplification effects from loan concentration in the affected areas due to limited data on credit exposures by location. GDP losses could be more considerable if a typhoon destroys vital infrastructure such as roads, ports, airports, and utility generation and distribution systems that have spillover effects to broader economic activities instead of, for example, residential areas. The overall impact on bank capital could become significant if all types of climate change risks and industry and company-level transmission channels are taken into account.

Alternative Scenarios and Estimates

This section checks the robustness of our analysis by comparing our scenarios with those provided by the NGFS. In 2021, NGFS released the second version of their climate scenarios, which included the estimated damage caused by extreme typhoons for the Philippines, among others. The NGFS and our scenarios are different in climate scenarios, return periods, time horizon, and exposure data.

- NGFS scenarios. Scenarios were developed by Climate Analytics using CLIMADA.²⁰ Future typhoon frequency and wind speed (climate scenario) is projected by applying scaling historical data with basin-based factors taken from an existing global-scale study by Knutson and others (2015).²¹ Similar to the

²⁰ CLIMADA is an open-source probabilistic climate assessment tool for physical risks. See details [here](#).

²¹ Knutson and others (2015) described the changes in tropical cyclone wind speed and frequency between 2000 and 2100 according to RCP 4.5 by basins.

study for the Philippines by Gallo and others (2018), the study projects that climate change reduces the average number of typhoons, while wind speeds rise for the Northeast Pacific Basin. The NGFS only provides the [expected damages from once-in-100-year typhoons](#). However, it gives all the pathways of damage rates from 2020 to 2100 as well as pathways under multiple climate scenarios in addition to RCP 8.5 by linearly interpolating the results under RCP 4.5.²² The exposure data (that is, the value and vulnerability of buildings and infrastructure by location) used to estimate damage from typhoons to physical capital in the CAT model are estimated using gridded GDP data.²³

- This paper. Our climate scenario is based on the Philippines-specific study under the RCP 8.5 (Gallo and others 2018) for the mid-21st century. We picked a specific point in time instead of the whole pathway, and only under the RCP 8.5 scenario, because the existing local climate and disaster scenarios were available only for RCP 8.5.²⁴ However, we examined the whole spectrum of return periods, including once in 10, 25, 50, 100, 250, and 500 years. Since we used typhoon simulation results using all the five climate models preferred by Gallo and others (2018), our approach incorporates climate model uncertainty. Our unique exposure data is built by the World Bank and the government of the Philippines, drawing on various sources of local information on buildings and infrastructure.

The NGFS scenarios show a comparable but somewhat lower impact of climate change on damage rates than do our estimates where projections overlap (Figure 6). Our estimate shows that physical capital damage from typhoons in our climate scenario rises by about 40 percent for once-in-a-100-year events by mid-21st century from 2020 (Table 1). As discussed in the disaster scenario section, this figure is the 90th percentile estimate. The median estimates implied by Figure 3, panel 1, is about one-third. These figures are nearly the same as NGFS estimates under the RCP 8.5 scenario at about 30 percent for median and above 40 percent for more tail estimates in 2060.

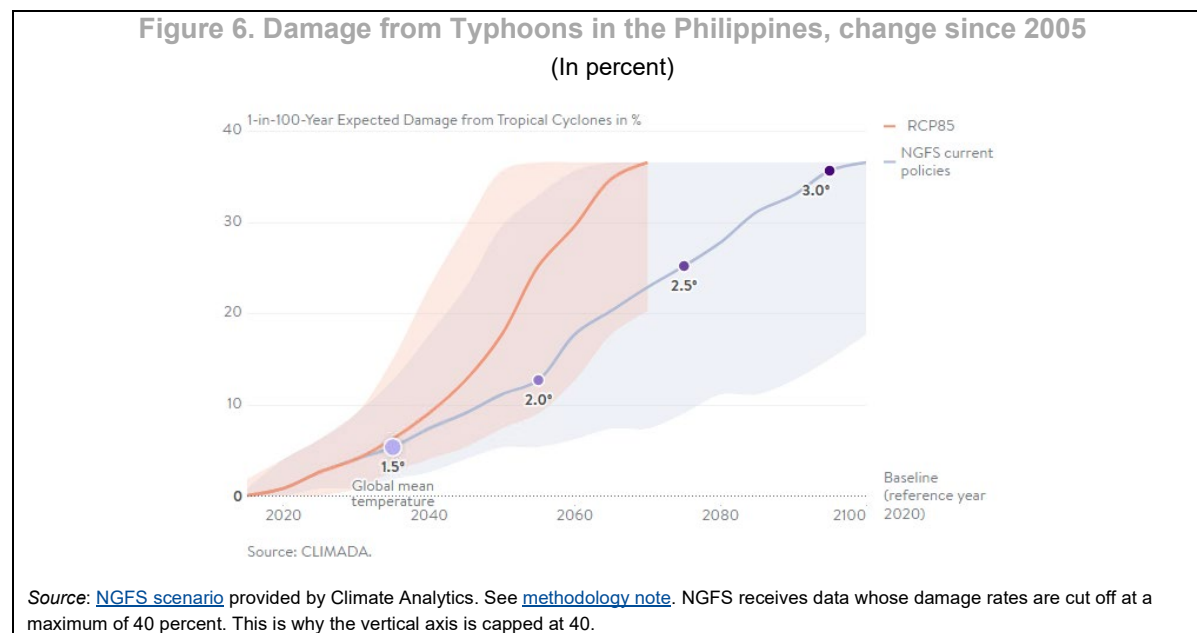
This finding is good news for both our methodology and NGFS approaches. It indicates the robustness of the results under the two different analytical strategies. The approaches are also complementary: our approach requires substantial country-specific data and climate model analyses but provide in-depth information on the considered hazards. When such data and models are not available, the NGFS scenario provides quick benchmark results.

The NGFS scenarios emphasize that the effects of climate change continue to grow throughout the 21st century. While the NGFS does not provide the whole pathways of damage rate under RCP 8.5, the pathways under the current (as of 2021) policies show that damage rate could double from 2060 (below 20 percent) to 2100 (about 40 percent), highlighting the importance of the time horizon for any stress testing exercises.

²² Climate Analytics created climate scenarios under RCP 4.5 by scaling historical tropical cyclone data with the scaling factor from Knutson and others (2015; see [methodology note](#)). As for climate scenarios under other RCPs, Climate Analytics applied a simple linear interpolation with respect to global temperatures to the RCP 4.5-based estimates, following Aznar-Siguan and others (2021).

²³ The gridded GDP data are taken from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) organized by an international network of climate-impact modelers. The project offers a framework for consistently projecting the impact of climate change across affected sectors and spatial scales. These data from ISIMIP are derived from national GDP estimates and spatially explicit population distribution information (see NGFS [methodology note](#)).

²⁴ Nonetheless, we could have, in principle, used the same linear extrapolation approach to obtain future hazard risk under other global warming assumptions.



Our approach, on the other hand, highlights the importance of considering more tail events at each point in time. Table 1 shows that the impact of climate change on damage rates appears to be generally higher for more tail events. Damage rate increases about 40 percent by mid-21st century for once-in-100-year typhoons and 55 and 68 percent respectively for once-in-250- and once-in-500-year typhoons.

The difference in GDP impacts follows the same pattern as damage rates (Table 2). Given the extent of uncertainties, our and NGFS's estimates for a given return period under the RCP 8.5 scenarios are in the same ballpark. But our estimates taking the 90th percentile point tend to show a somewhat higher impact for rarer events (250- and 500-year return periods), even compared to NGFS's upper bound estimates. The difference from NGFS's current policy scenario is comparable to our estimates for 25-year return period events but grows to about 40 percent for 500-year return period events.

Table 2. Difference between NGFS and Authors' estimates: Damage Rate and GDP (In percent)										
	Climate scenario: damage rate					Macroeconomic scenario: peak GDP decline				
Climate scenario	Author	NGFS 2021 ³			Author	Author	NGFS 2021			Author
	Current	NGFS current policies	RCP 8.5		RCP 8.5	Current	NGFS current policies	RCP 8.5		RCP 8.5
Time of estimate	2019	2060			Mid-21st century	2020	2060			Mid-21st century
Projected increase in damage ¹	...	17.6 median	29.5 median	36.5 upper bound	20-68 90 th pct.	...	17.6 median	29.5 median	36.0 upper bound	20-68 90 th pct.
Return period	...	Same increase across return periods ²			Period-specific
10	0.52	0.6	0.7	0.7	0.8	-0.9	-1.0	-1.1	-1.2	-1.3
25	0.92	1.1	1.2	1.3	1.1	-1.5	-1.8	-2.0	-2.1	-1.8
50	1.42	1.7	1.8	1.9	2.0	-2.3	-2.8	-3.0	-3.2	-3.3
100	2.23	2.6	2.9	3.0	3.1	-3.7	-4.3	-4.8	-5.0	-5.1
250	3.68	4.3	4.8	5.0	5.7	-6.1	-7.1	-7.9	-8.0	-9.4
500	5.03	5.9	6.5	6.9	8.5	-8.7	-9.8	-10.7	-11.3	-14.0

Source: [NGFS](#) based on CLIMADA and Climate Analytics, and authors.

Note: The current scenarios and authors' estimates/scenarios are the same as Table 1.

1/ Both NGFS and authors' estimates have a range reflecting model and simulation uncertainties. For this table, we took median estimates as well as upper bound estimates, while our scenarios were built on the 90th percentile point estimates.

2/ NGFS only provides estimates for once-in-100-year events. The same change in damage rates is applied to all the other return periods.

3/ NGFS scenarios provide only the increase of damage, not the damage rates, so we used our estimates of current damage rates and applied the percentage increase of damages shown in Figure 4 to calculate damage rates under NGFS scenarios.

However, the difference across distinct global climate scenarios (NGFS current policies and RCP 8.5) is likely to be much larger toward 2100 than shown in Table 2. Figure 6 suggests that the damage rate difference across global climate scenarios tends to grow over time, while model uncertainties (the band around the median for respective scenarios) tend to matter more at mid-21st century. This observation suggests that our stress tests, focusing on mid-21st century climate change projections, should be interpreted carefully. The results should be used cautiously when extending the discussion of climate change risks and financial stability over the long-time horizon.

Conclusion

This paper examined the potential impact of physical risks from climate change on banks in an emerging market economy, using a novel method to build scenarios based on climate science and CAT risk models. Our work contributes to the rapidly growing literature on financial stability analysis of climate change risks in several ways:

First, by tailoring to the country in question. Instead of IAMs with somewhat arbitrary and non-specialized damage functions or more generic CAT risk models, our approach is tailored to the Philippines. In particular, we used unique detailed asset databases and insurance-industry standard vulnerability functions to produce

tailored probabilistic assessments of tail-risks to produce physical capital damage rates. We also used localized climate models that produced country-specific projections of future typhoon frequency and wind speed under RCP 8.5, unlike other studies that use projections for broader regions such as NGFS scenarios using basin-based typhoon projection.

Second, by coupling a standard CAT model with climate models. A standard CAT risk model does not account for climate change. Building a CAT model using projected future disaster parameters from climate models is an emerging tool in the insurance industry. However, to our knowledge, this paper is the first one applying such an approach to bank stress tests.

Third, by providing detailed analysis over various tail points of damages from disasters. Although our study focused narrowly on the wind-related destruction from typhoons, we examined the impact under multiple tail points ranging from once in 10- to 500-year events enabled by the probabilistic capability of the CAT model. Examining different tail points seems essential in financial stability analysis, as our results show a non-linear impact of climate change for rarer events.

Fourth, by applying this study to an emerging market economy. Available bank stress testing exercises that take into account climate change risks are predominantly undertaken within advanced economies so far (FSI 2021). Nonetheless, climate change is likely to cause more physical damage to emerging market and developing economies close to the equator (IMF 2017). We think it is important to expand the research on these economies, both for the sake of these economies as well as to better understand the impact of climate change on global financial stability.

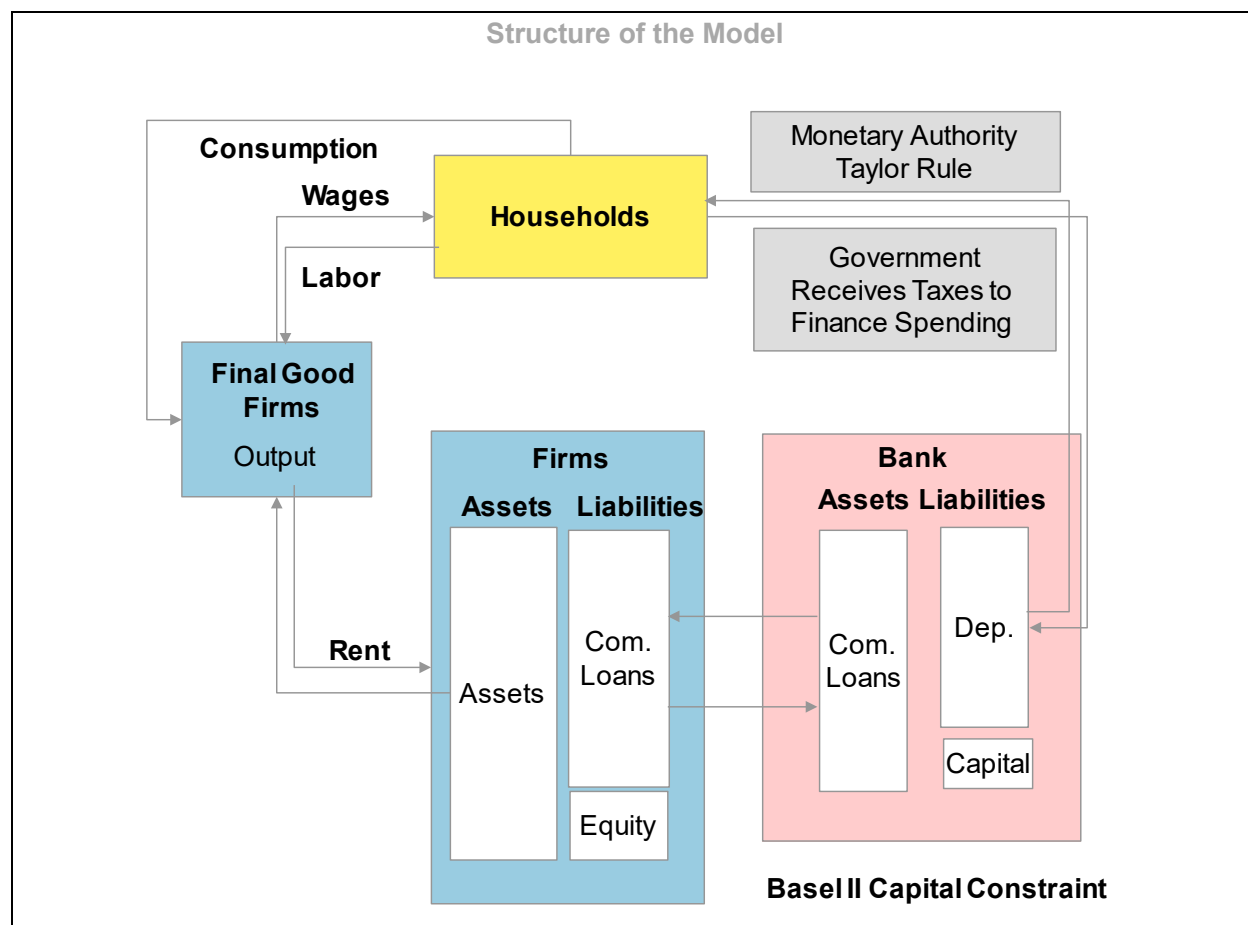
The results show that the impact of climate change on financial stability through typhoons differs substantially depending on models, the severity of hazards (return period), and the number of hazards considered (compound risks). Focusing only on damages from a typhoon's wind, the extreme tail (once in 100 or more years) impact from climate change up to the mid-21st century on the macroeconomy (GDP) could be systemic in the Philippines already and would worsen substantially with climate change. But the impact is not systemic under less extreme disasters (such as 25-year return period events—the frequency used by IMF-WB FSAP systemic stress tests for banks). Despite systemic macroeconomic impact under extreme tail disasters, the effects on bank capital appear largely manageable, partly because our starting point data were as of end-2019 when banks were fairly healthy and economic vulnerabilities were limited. Yet, a compound risk with another extreme disaster such as a pandemic could systemically distress the banking sector. On the other hand, the chronic impact of climate change on financial stability appears small. Their annual impact on GDP is small, which implies that banks are likely to be able to absorb the impact with their annual profits alone without using their capital buffer. Over the long run, the cumulative chronic impact on GDP is substantially larger than those of rare extreme typhoons. But banks' buffers, including cumulative profits in the long run, are also much higher than immediately available buffers for withstanding short-term acute shocks (i.e., capital buffers at the time of disaster and a few years' profits).

The results should be interpreted cautiously because our exercise is far from comprehensive and subject to deep uncertainty. While we shed new light on climate change and financial stability issues, there are several areas where we could not investigate thoroughly due to technical and data constraints. For instance, our work focused only on macroeconomic channels, as data constraints limited our ability to analyze differentiated impact by location and industry, or other micro-level channels such as collateral valuation. We focused narrowly on the damage from typhoons' wind due to the limitation of current climate model scenarios and the lack of access to a storm surge model for the Philippines. Another CAT model is necessary to consider the

impact of floods. A completely different set of models is needed to consider chronic impacts of climate change, including the effects on crop yields and on sea-level rise, as well as the chronic impact of higher temperatures on human productivity. Moreover, any research on climate change should embrace different types of uncertainties, including risk, ambiguity (deep uncertainty), and model misspecification (Hansen, 2021). More research will be needed before we can form a comprehensive understanding of climate change and its impact on financial stability, as well as what might be appropriate policy measures.

Annex I. Macro Scenario Model¹

The model is a simplified version of Lipinsky and Miescu (2020) and adapted for the economic and financial structure of the Philippines. It has household, firms, banks, monetary authority, and the government with the following interactions.



Households

Households maximize expected lifetime utility $E_0 \sum_{t=0}^{\infty} \beta^t U_t$, subject to a budget constraint. Households obtain utility from consumption c_t , subject to internal habit formation $h > 0$, and disutility from sending n_t members to work. Their preferences take the following form:

$$U_t = \frac{z_{c,t}(c_t - hc_{t-1})^{1-\sigma}}{1-\sigma} - \frac{\tau_n n_t^{1+\phi}}{1+\phi}$$

We call $z_{c,t}$ a demand shock, because it increases the demand for consumption and induces households to work more. Regarding the budget constraint, households consume c_t , and put savings d_t in a bank account.

¹ Additional details are available upon request from authors.

On the income side, they receive wage income $w_t n_t$ in return for providing labor, interest income $\frac{R_{d,t-1}}{\pi_t} d_{t-1}$ on savings, $\Pi_{i,t} = q_t i_t - i_t(1 + S)$ from capital goods producers that provide capital goods i_t to firms at price q_t , and face quadratic cost of producing capital, and profits $\Pi_{y,t}$ from final good firms.

$$c_t + d_t = w_t n_t + \frac{R_{d,t-1}}{\pi_t} d_{t-1} + \Pi_{i,t} + \Pi_{y,t}$$

The optimization problem is expressed as follows.

$$\begin{aligned} \max \mathcal{L} = E_0 \sum_{t=0}^{\infty} \beta^t & \left[\frac{z_{c,t}(c_t - hc_{t-1})^{1-\sigma}}{1-\sigma} - \frac{\tau_n n_t^{1+\phi}}{1+\phi} \right] \\ & - \lambda_t \left[c_t + d_t - \left(w_t n_t + \frac{R_{d,t-1}}{\pi_t} d_{t-1} + q_t i_t - i_t \left(1 + S \left(z_{i,t} \frac{i_t}{i_{t-1}} \right) \right) \right) + \Pi_{y,t} \right] \end{aligned}$$

The first order conditions with respect to consumption c_t , labor n_t , saving d_t , and investment i_t are:

$$\begin{aligned} \partial c_t: z_{c,t} & \left((c_t - hc_{t-1})^{-\sigma} - h\beta E_t \left[\frac{z_{c,t+1}}{z_{c,t}} (c_{t+1} - hc_t)^{-\sigma} \right] \right) - \lambda_t = 0 \\ \partial n_t: & -\tau_n n_t^\phi + \lambda_t w_t = 0 \\ \partial d_t: & -1 + \beta E_t \left[\frac{\lambda_{t+1}}{\lambda_t} \frac{R_{d,t}}{\pi_{t+1}} \right] = 0 \\ \partial i_t: & q_t - \left(1 + S \left(z_{i,t} \frac{i_t}{i_{t-1}} \right) \right) + S' \left(z_{i,t} \frac{i_t}{i_{t-1}} \right) z_{i,t} \frac{i_t}{i_{t-1}} + \beta E_t \left[\frac{\lambda_{t+1}}{\lambda_t} S' \left(z_{i,t+1} \frac{i_{t+1}}{i_t} \right) z_{i,t+1} \left(\frac{i_{t+1}}{i_t} \right)^2 \right] = 0 \\ & S \left(z_{i,t} \frac{i_t}{i_{t-1}} \right) = \frac{\phi_i}{2} \left(z_{i,t} \frac{i_t}{i_{t-1}} - 1 \right)^2 \end{aligned}$$

Firms

Firms invest $q_t k_t$ in productive assets k_t . Firms finance assets with commercial loans l_t from the bank, and with equity $n_{F,t} = q_t k_t - l_t$. Next period, they receive a gross return on assets equal to $R_{k,t+1} = r_{k,t+1} + (1 - \delta)q_{t+1}$, consisting of a rental rate of capital $r_{k,t+1}$ and the value of assets after depreciation $(1 - \delta)q_{t+1}$, and pay a share Γ_{t+1} of the earnings to the bank in return for the loans. Firms' cashflow is:

$$-n_{F,t} + E_t \left(M_{t+1} \left(R_{k,t+1} k_t (1 - \Gamma_{t+1}) \right) (1 - \tau) \right)$$

Banks

The bank intermediates funds between households and firms. It receives funds d_t from households, promising a return $R_{d,t}$, and provides l_t commercial loans to firms. The remainder is financed with equity $n_{B,t} = l_t - d_t$. Next period the bank receives the share Γ_{t+1} of earnings $R_{k,t+1}k_t$ from firms. A part of the firms' default, incurring default costs $R_{k,t+1}k_t\mu\Delta_{t+1}$ for the bank. The bank's cashflow and objective is:

$$-n_{B,t} + E_t \left(M_{t+1} \left(R_{k,t+1}k_t(\Gamma_{t+1} - \mu\Delta_{t+1}) - \frac{R_{d,t}}{\pi_{t+1}}d_t \right) (1 - \tau) \right)$$

While the firm sector cannot go under ($R_{k,t+1}k_t(1 - \Gamma_{t+1}) > 0$), the value of assets of the bank may fall below the value of liabilities. To shield the bank from default, it adopts a Basel II capital constraint:

$$\frac{R_{k,t+1}}{\pi_{t+1}}k_t(\overline{\Gamma_{t+1}} - \mu\overline{\Delta_{t+1}}) - \frac{R_{d,t}}{\pi_{t+1}}d_t \geq 0$$

Even if the gross return $R_{k,t+1}$ falls to $\underline{R_{k,t+1}} \equiv \theta_t E_t(R_{k,t+1})$, the bank remains solvent. We call θ_t value-at-risk shock, because it quantifies the downside risk for the bank.

The optimization problem of the bank is to maximize its cashflow subject to the Basel capital constraint and the participation constraint of firms,

$$\begin{aligned} \max_{\{l_t, n_{B,t}, R_{l,t}\}} \mathcal{L} = & -n_{B,t} + E_t \left(M_{t+1} \left(\frac{R_{k,t+1}}{q_t} (n_{F,t} + l_t) (\Gamma(\varepsilon_{t+1}^*) - \mu\Delta(\varepsilon_{t+1}^*)) - \frac{R_{d,t}}{\pi_{t+1}}d_t \right) (1 - \tau) \right) \\ & + \lambda_t^V E_t \left(M_{t+1} \left(\frac{R_{k,t+1}}{q_t} (n_{F,t} + l_t) (\Gamma(\overline{\varepsilon_{t+1}}) - \mu\Delta(\overline{\varepsilon_{t+1}})) - \frac{R_{d,t}}{\pi_{t+1}}d_t \right) \right) \\ & + \lambda_{F,t} \left(-n_{F,t} + E_t \left(M_{t+1} \left(\frac{R_{k,t+1}}{q_t} (n_{F,t} + l_t) (1 - \Gamma(\varepsilon_{t+1}^*)) \right) (1 - \tau) \right) \right) \end{aligned}$$

where $d_t = l_t - n_{B,t}$.

To build intuition, it should be noted that income of firms and the bank are taxed at rate $\tau > 0$, while households don't pay taxes on deposits. Accordingly, financial intermediation yields a return equal to $\frac{R_{d,t}}{\pi_{t+1}}d_t$, or making use of the Basel II capital constraint:

$$\tau \left(\frac{R_{k,t+1}}{\pi_{t+1}}k_t(\overline{\Gamma_{t+1}} - \mu\overline{\Delta_{t+1}}) \right)$$

Commercial loans are chosen optimally trading off the benefit of financial intermediation $\tau \left(\frac{R_{k,t+1}}{\pi_{t+1}}k_t(\overline{\Gamma_{t+1}} - \mu\overline{\Delta_{t+1}}) \right)$ versus the cost of default $-R_{t+1}k_t\mu\Delta_{t+1}(1 - \tau)$.

We can show that Γ_{t+1} and Δ_{t+1} depend on ε_{t+1}^*

$$\varepsilon_{t+1}^* = \frac{R_{l,t}l_t}{\pi_{t+1}R_{k,t+1}k_t}$$

$$\Gamma(\varepsilon_{t+1}^*) \equiv \Delta(\varepsilon_{t+1}^*) + \varepsilon_{t+1}^*(1 - F(\varepsilon_{t+1}^*)), \Gamma'(\varepsilon_{t+1}^*) = 1 - F(\varepsilon_{t+1}^*)$$

$$\Delta(\varepsilon_{t+1}^*) \equiv \int_0^{\varepsilon_{t+1}^*} \varepsilon_{t+1} f(\varepsilon_{t+1}) d(\varepsilon_{t+1}), \Delta'(\varepsilon_{t+1}^*) = f(\varepsilon_{t+1}^*) \varepsilon_{t+1}^*$$

and $\overline{\Gamma_{t+1}}$ and $\overline{\Delta_{t+1}}$ on $\overline{\varepsilon_{t+1}}$

$$\overline{\varepsilon_{t+1}} = \frac{R_{l,t} l_t}{\theta_t \pi_{t+1} R_{k,t+1} k_t}$$

such that choice of the lending rate implies the marginal tradeoff of the higher cost of default versus the higher benefit of financial intermediation.

$$\frac{\partial \left(-R_{t+1} k_t \mu \Delta_{t+1} (1 - \tau) + \tau \left(\frac{R_{k,t+1}}{q_t} k_t (\overline{\Gamma_{t+1}} - \mu \overline{\Delta_{t+1}}) \right) \right)}{\partial R_{l,t}} \\ = (-\mu f(\varepsilon_{t+1}^*) \varepsilon_{t+1}^* (1 - \tau) + \tau (1 - F(\overline{\varepsilon_{t+1}}) - \mu f(\overline{\varepsilon_{t+1}}) \overline{\varepsilon_{t+1}})) l_t / \pi_{t+1}$$

Furthermore, it should be noted that Γ_{t+1} and Δ_{t+1} as well as $\overline{\Gamma_{t+1}}$ and $\overline{\Delta_{t+1}}$ depend on $\sigma_{F,t}$, as emphasized by Christiano, Motto, and Rostagno (2014), called idiosyncratic or default risk shock. A higher value of $\sigma_{F,t}$ results in more mass in the tail of the distribution, a higher value of $F(\varepsilon_{t+1}^*)$, and more firm defaults.

The solution to banks' optimization has the following characteristics.

The bank provides commercial loans (∂l_t) such that the return equals the cost:

$$\partial l_t: E_t \left(M_{t+1} \left(\frac{R_{k,t+1}}{q_t} X_{t+1} - \frac{R_{d,t}}{\pi_{t+1}} (1 - \tau + \lambda_t^V) \right) \right) = 0$$

The standard first order condition in model with capital accumulation is $1 = E_t \left(M_{t+1} \left(\frac{R_{k,t+1}}{q_t} \right) \right)$ or

$E_t \left(M_{t+1} \left(\frac{R_{k,t+1}}{q_t} - \frac{R_{d,t}}{\pi_{t+1}} \right) \right) = 0$. In contrast, the factor X_{t+1} enters here, including the cost of default $-\mu \Delta(\varepsilon_{t+1}^*)$ and the benefit of financial intermediation $\lambda_t^V \theta_t (\Gamma(\overline{\varepsilon_{t+1}}) - \mu \Delta(\overline{\varepsilon_{t+1}}))$:

$$X_{t+1} \equiv \left(\lambda_{F,t} (1 - \Gamma(\varepsilon_{t+1}^*)) + (\Gamma(\varepsilon_{t+1}^*) - \mu \Delta(\varepsilon_{t+1}^*)) (1 - \tau) + \lambda_t^V \theta_t (\Gamma(\overline{\varepsilon_{t+1}}) - \mu \Delta(\overline{\varepsilon_{t+1}})) \right)$$

The bank chooses equity ($\partial n_{B,t}$), internalizing that more equity loosens the Basel II capital constraint.

$$\partial n_{B,t}: -1 + E_t \left(M_{t+1} \frac{R_{d,t}}{\pi_{t+1}} (1 - \tau + \lambda_t^V) \right) = 0$$

The bank chooses commercial loan rates ($\partial R_{l,t}$) such that X_{t+1} is maximized and invariant to changes in the default threshold that is $\frac{\partial X_{t+1}}{\partial \varepsilon_{t+1}^*, \varepsilon_{t+1}} = 0$. The bank chooses the commercial loan lending rate equating the marginal cost of more defaults to the marginal benefit of financial intermediation.

$$\partial R_{l,t}: E_t \left(\frac{M_{t+1}}{\pi_{t+1}} \left(\left(\lambda_{F,t} (-(1 - F(\varepsilon_{t+1}^*))) + (1 - F(\varepsilon_{t+1}^*) - \mu f(\varepsilon_{t+1}^*) \varepsilon_{t+1}^*) \right) (1 - \tau) \right. \right. \\ \left. \left. + \lambda_t^V (1 - F(\overline{\varepsilon_{t+1}}) - \mu f(\overline{\varepsilon_{t+1}}) \overline{\varepsilon_{t+1}}) \right) \right) = 0$$

Stock Price Gaps

Firms accumulate net worth $n_{F,t}$ out of retained earnings, distributing a share γ_D of earnings and receiving a fixed equity injection equal to ω .

$$n_{F,t} = R_{k,t} k_{t-1} (1 - \Gamma(\varepsilon_t^*)) (1 - \tau) (1 - \gamma_D) + \omega$$

However, firms' target net worth $n_{F,t}^*$ results from choosing net worth optimally:

$$\partial n_{F,t} : \lambda_{F,t} = 1$$

Comparing the solutions between realized and target net worth provides deviations from the optimum. For the stock price, the gap is called stock price gap:

$$spg = \frac{q_t - q_t^*}{q_t^*}$$

Equilibria

In the optimal solution ($\partial n_{F,t} : \lambda_{F,t} = 1$), the participation constraint of firms determines $n_{F,t}$, the optimality condition with respect to l_t determines k_t and hence $l_t = q_t k_t - n_{F,t}$, and the Basel II capital constraint determines d_t and hence $n_{B,t} = l_t - d_t$. The optimality condition with respect to $n_{B,t}$ together with the optimality condition of households with respect to d_t imply $\lambda_t^V > 0$.

In the realized (suboptimal) model solution, $n_{F,t}$ is given through the exogenous law of motion. Then, the participation constraint of firms determines k_t and hence $l_t = q_t k_t - n_{F,t}$. The optimality condition with respect to l_t determines $\lambda_{F,t}$, which is time varying. While d_t and λ_t^V are determined as above.

The Financial System and Market Clearing

An agent representative for the financial sector smooths dividends $c_{FS,t}$ by maximizing lifetime utility

$$E_0 \sum_{t=0}^{\infty} \beta^t U_t^{FS}$$

$$U_t^{FS} = \frac{z_{c,t} (c_{FS,t} - h c_{FS,t-1})^{1-\sigma}}{1-\sigma}$$

and aggregates income across firms and the bank. The budget constraint of the financial sector is:

$$c_{FS,t} + q_t k_t - d_t = \left(R_{k,t} k_{t-1} (1 - \mu \Delta_t) - \frac{R_{d,t-1}}{\pi_t} d_{t-1} \right) (1 - \tau)$$

and the stochastic discount factor is:

$$M_{t+1} = \beta \frac{\lambda_{FS,t+1}}{\lambda_{FS,t}}$$

where $\lambda_{FS,t}$ is the LaGrange multiplier associated to the budget constraint.

Final Good Firms, Inflation, and Monetary Policy

Final good firms rent capital $k_{i,t-1}$ from firms, hire workers $n_{i,t}$ from households, and choose prices $p_{i,t}$, subject to quadratic adjustment cost,

$$\begin{aligned} \frac{\varphi}{2} \left(\frac{p_{i,t}}{p_{i,t-1}} - 1 \right)^2 y_t &= \frac{\varphi}{2} \left(\pi_t \frac{p_{i,t}}{p_{i,t-1}} - 1 \right)^2 y_t, \quad \pi_t \equiv \frac{p_t}{p_{t-1}}, \quad p_{i,t} \equiv \frac{p_{i,t}}{p_t}, \quad \eta_t = \eta_{ss} z_{\eta,t}, \\ \max \left\{ \Pi_{y,i,t} &= p_{i,t} y_{i,t} - r_t k_{i,t-1} - w_t n_{i,t} - \frac{\varphi}{2} \left(\pi_t \frac{p_{i,t}}{p_{i,t-1}} - 1 \right)^2 y_t \right\} \\ y_{i,t} &= k_{i,t-1}^\alpha (z_{y,t} n_{i,t})^{1-\alpha} \\ y_{i,t} &= p_{i,t}^{-\eta_t} y_t \end{aligned}$$

resulting in the following optimization problem:

$$\max \left\{ p_{i,t} y_{i,t} - r_t k_{i,t-1} - w_t n_{i,t} - \frac{\varphi}{2} \left(\pi_t \frac{p_{i,t}}{p_{i,t-1}} - 1 \right)^2 y_t + p_{m,i,t} \left(k_{i,t-1}^\alpha (z_{y,t} n_{i,t})^{1-\alpha} - y_{i,t} \right) + v_{i,t} (p_{i,t}^{-\eta_t} y_t - y_{i,t}) \right\}$$

A symmetric equilibrium implies the following first order conditions, after making use of $\partial y_{i,t}$: $v_t = 1 - p_{m,t}$,

$$\begin{aligned} \partial k_{i,t-1}: \quad r_t &= p_{m,t} \alpha \frac{y_t}{k_{t-1}} \\ \partial n_{i,t}: \quad w_t &= p_{m,t} (1 - \alpha) \frac{y_t}{n_t} \\ \partial p_{i,t}: \quad p_{m,t} &= 1 - \frac{1}{\eta_t} \left(1 - \varphi \pi_t (\pi_t - 1) + \varphi \beta E_t \left(\frac{\lambda_{t+1}}{\lambda_t} \pi_{t+1} (\pi_{t+1} - 1) \frac{y_t}{y_{t-1}} \right) \right) \end{aligned}$$

The monetary authority sets interest rates according to a Taylor rule:

$$\frac{R_{d,t}}{R_{d,ss}} = \left(\frac{R_{d,t-1}}{R_{d,ss}} \right)^{\gamma_R} \left(\frac{\pi_t}{\pi_{ss}} \right)^{(1-\gamma_R)\gamma_\pi} \left(\frac{y_t}{y_{ss}} \right)^{(1-\gamma_R)\gamma_y} e^{\sigma_m \epsilon_{m,t}}$$

In a simple real-business-cycle model without inflation, the problem would simplify. Final good firms would rent capital k_{t-1} from firms and hire workers n_t from households.

$$\begin{aligned} \max \{ y_t - r_t k_{t-1} - w_t n_t \} \\ y_t &= k_{t-1}^\alpha (z_{y,t} n_t)^{1-\alpha} \end{aligned}$$

The first order conditions with respect to capital and labor would yield equations for the return on capital r_t and wages w_t :

$$\begin{aligned} \partial k_{t-1}: \quad r_t &= \alpha \frac{y_t}{k_{t-1}} \\ \partial n_t: \quad w_t &= (1 - \alpha) \frac{y_t}{n_t} \end{aligned}$$

Calibrated Parameters

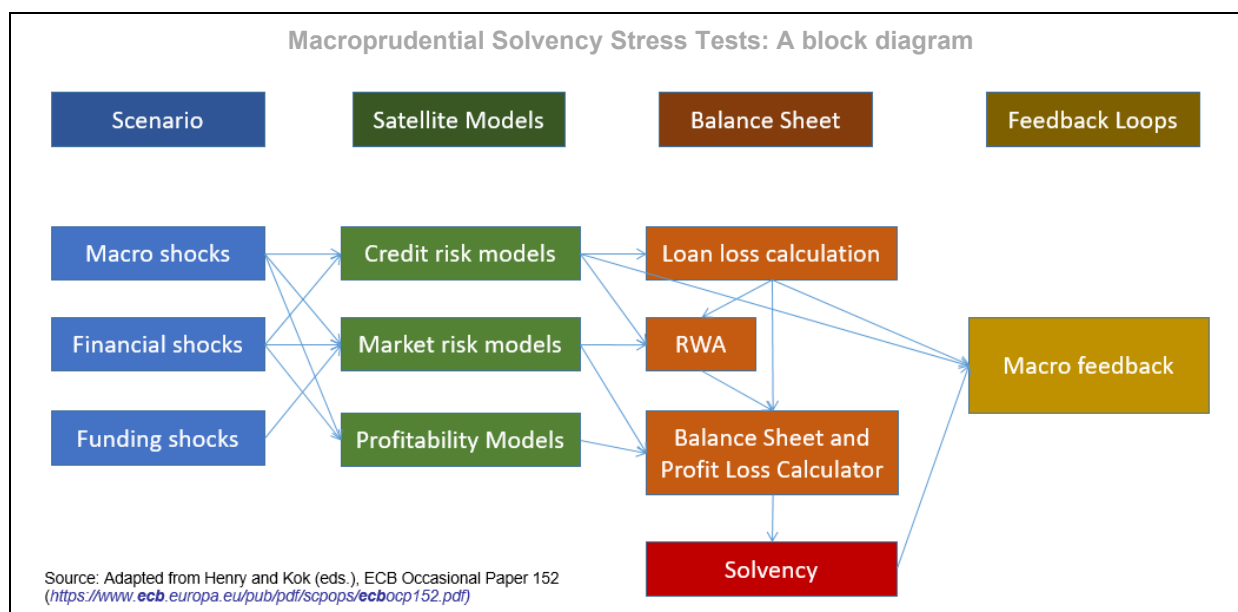
Parameters	Description	Values
α	power on capital in production function	0.300
β	discount factor	0.990
δ	depreciation rate of capital	0.025
h	habit in consumption	0.750
ϕ	Frisch elasticity of labor supply	1.000
τ_n	disutility of supplying labor	4.000
ϕ_i	investment adjustment cost	3.000
φ	price adjustment cost	0.750
η_{ss}	steady-state price elasticity	1.500
μ	cost of default / screening cost	0.400
τ	additional discount associable to taxes	0.030
γ_D	dividend payout	0.030

The remaining parameters and the magnitudes of shocks were estimated as described in Lipinsky and Miescu (2020).

Annex II. Bank Stress Test Model¹

The scenario-based assessment follows the standard FSAP stress test approach using balance sheet information. The solvency stress test assesses whether banks have adequate capital buffers to withstand a set of macro-financial shocks envisioned under the four three-year horizon scenarios. The diagram below illustrates selected elements of the solvency stress testing framework. Scenarios influence the credit risk, market risk, and profitability of individual institutions. This, in turn, has an impact on banks' balance sheets and profit and losses via changes in the loan loss provisions, risk-weighted assets (RWAs), market gain/losses, interest income, and non-interest income. Post stress capital is calculated by adjusting the initial capital (C_0) of each institution with the stressed income ($Income^*$) and the stressed RWA (RWA^*), as follows:

$$CR^* = \frac{C_0 + Income^*}{RWA^*}$$



The tests assume a quasi-static balance sheet. The allocation of assets and the composition of funding sources remain the same as of the latest actual observation. Gross exposures in bank balance sheets, such as loans and holdings of debt securities, are assumed to grow in line with nominal GDP growth. Besides, banks are able to build capital buffers only through retained earnings (i.e., no new equity issuance).

Credit risk satellite models link the macro-financial scenario to a proxy probability of default (PD), using quarterly information for the period 2005–19. Since bank credit risk data only indicate performing or nonperforming and flows into and out of NPLs, proxy PDs are calculated as annualized quarterly flows into new NPLs over the stock of performing loans at the beginning of the quarter. For the estimation, all the possible combinations of key macroeconomic variables (e.g., real GDP growth, unemployment rate, short-term interest

¹ Additional details are available upon request from authors. Also, see 2021 Philippines FSAP Technical Note on Risk Assessment of Banks, Non-financial Corporates, and Macro-Financial Linkages (IMF, forthcoming).

rates, term spread, stock prices, exchange rate), as well as different lag structures, are considered. Final models are selected based on in-sample fit and significance of long-run multipliers among a pool of models that comply with sign constraints in line with economic theory. The model is estimated, using aggregate PD, since the bank-level information on NPL flows were noisy and available only for shorter horizon. The aggregate PD is then mapped to individual bank PDs proportional to their initial PDs. The mapping is done by using the standard score (z-score in a standard normal distribution) of aggregate PDs and of individual banks' starting PDs.² This approach guarantees that the projected PDs of individual banks remain within the [0, 1] range. LGDs are assumed to be consistent with historical aggregate coverage ratios and kept constant throughout the test horizon and across scenarios. In line with history, a part of NPLs are assumed to be cured back to performing, with a cure rate well below the historical average to be conservative.

The market risk module assesses the risk associated with valuation adjustments from changes in asset prices, interest rates, and exchange rates. The adjustment is applied to banks' securities portfolios and existing open positions in foreign currency in their balance sheets. For available-for-sales (AfS) and held-for-trading (HfT) securities, market losses/gains are estimated following a mark-to-market approach. A modified duration formula is employed to reevaluate exposures as a function of their reported residual duration and the relevant bond yield assumption under the scenarios. Trading losses from HfT securities are considered realized losses, affect net income, and are subject to taxation and dividend payout. Unrealized gains/losses from AfS securities affect other comprehensive income (OCI). However, they are not subject to taxation. Therefore, valuation changes in AfS securities affect capital one to one. For HtM securities, the framework uses a credit risk approach. Provisions are made to cover expected loss as asset quality deteriorates. Finally, valuation changes in open foreign positions are estimated based on fluctuations of the exchange rate under the scenarios (i.e., Net Open Position in FX × change in the exchange rates).

Interest rate risk on the banking book (IRRBB) is assessed using time-to-repricing buckets. Banks are exposed to maturity transformation risk as they lock in rates on assets for more extended periods than rates on liabilities. The impact of interest rate risk on net interest income is estimated by measuring the gaps between assets and liabilities that reprice in each period, up to the end of the three-year stress test horizon. Banks' maturity profile is assumed to remain the same over the stress testing period. In addition, the exercise applies interest margin shocks. Consistent with a decrease in the interest margin observed during the Asian financial crisis (AFC), the test assumes a decline of interest margin.

In addition, the exercise applies interest margin shocks. Consistent with a decrease in the interest margin observed during the AFC, the test assumes a shock on the interest margin. The shock is taken as a fraction of the shock experienced during the AFC, which had a V shape with a peak of 80 percent in the second year. The severe adverse scenario assumes a quarter of the AFC shocks, while other scenarios assume milder shocks. The COVID macro scenarios consider more moderate margin shocks than the AFC because of the more benign financial condition observed so far. In particular, the central bank managed to cut interest rates, unlike the AFC period, which reduces the pressures on margins from increases in funding costs. Thus, the reduction

² For instance, the PD paths for each UKB are given by the formula $PD_{i,t} = \Phi \left(\Phi^{-1}(PD_{i,0}) + \left(\Phi^{-1}(PD_{UKB,t}) - \Phi^{-1}(PD_{UKB,0}) \right) \right)$, where $\Phi(\cdot)$ is the cumulated distribution function (CDF) of a the Normal Distribution and $\Phi^{-1}(\cdot)$ is the inverse CDF.

in interest margin is assumed to be driven by a decrease in lending rates and shocks are applied to the fraction of loans that mature and are repriced in each period.

Net income (profit and loss) is projected, incorporating all the risk factors in the stress test. The net interest income accounts for changes in balance sheet size, reduction in income due to increases in non-performing loans, changes due to IRRBB, and effects of interest margin shocks. Loan loss provisions are determined by the evolution of credit risk on loans and HtM securities. Trading income accounts for gains and losses associated with HfT securities and FX-open positions. Other on the income statement, including non-interest income and non-interest expense, are assumed to remain constant as a proportion of interest-earning assets over the stress testing period. The income tax rate is set at 30 percent.

Dividend payout, crucial for banks' ability to recover from shocks, depends on bank profits and bank types. Dividends are assumed to be paid only if net income after taxes is positive. The dividend payout ratio are set in line with individual banks' history of payout.

The risk-weighted assets (RWAs) changes in response to the changes in credit risks, following the Basel III standardized approach. There are three main components driving shifts in RWAs for credit risk. The first component reflects a decrease in risk weights (to zero) generated by the flow of provisions related to new NPLs. The second component shows the increase in risk weights resulting from the non-provisioned part of new NPLs, which, according to the Basel III standardized approach, are subject to a 150 percent risk weight. The third component reflects changes in risk weights as NPLs cure. In addition, RWAs grow in line with balance sheet growth, which is set at the nominal GDP growth rate (static balance sheet assumption).

Annex III. Financial Soundness Indicator of the Philippines

	(in percent)					
	2015	2016	2017	2018	2019	2020*
Capital adequacy						
Regulatory capital to risk-weighted assets	15.3	14.5	14.4	14.9	15.2	15.0
Regulatory tier 1 capital to risk-weighted assets	12.8	12.6	12.7	13.3	14.0	13.9
Capital to total assets	10.5	10.4	10.6	11.3	11.5	11.0
Non-performing loans net of provisions to capital	3.1	3.0	3.1	3.5	4.6	5.1
Net open position in foreign exchange to capital	2.4	2.0	7.9	4.7	5.8	3.5
Gross asset position in financial derivatives to capital	1.7	1.8	1.6	1.8	1.2	1.6
Gross liability position in financial derivatives to capital	0.0	0.0	0.0	0.1	0.4	0.6
Asset quality						
Nonperforming loan to gross loans	1.9	1.7	1.6	1.7	2.0	2.2
Specific provisions to nonperforming loans	70.1	69.7	66.9	63.2	58.0	57.6
Earnings and profitability						
Return on assets	1.4	1.4	1.3	1.3	1.5	1.4
Return on equity	13.8	13.7	13.6	12.7	13.9	13.0
Interest margin to gross income	70.7	69.2	73.9	75.2	74.0	76.3
Trading income to total income	5.7	8.3	4.3	3.2	7.8	9.4
Noninterest expenses to gross income	61.3	60.8	60.9	62.2	58.7	53.9
Personnel expenses to non-interest expenses	37.6	36.7	36.6	35.4	34.5	33.6
Liquidity and funding						
Liquid assets to total assets	38.8	35.6	32.9	32.6	32.1	30.6
Liquidity assets to short-term liabilities	60.6	54.6	51.8	50.7	48.8	46.9
Non-interbank loans to customer deposits	76.9	76.3	79.6	82.7	85.2	83.6
Sensitivity						
Foreign currency denominated loans to total loans	11.9	11.9	11.1	10.9	10.7	11.1
Foreign currency denominated liabilities to total liabilities	20.3	20.7	20.2	20.1	19.6	19.2
Real estate markets						
Residential real estate loans to total loans	7.2	7.3	7.2	7.1	7.3	7.4
Commercial real estate loans to total loans	13.9	14.3	14.1	12.3	13.2	13.7
Household Indebtedness						
Loans to households to total loans	17.4	17.8	17.9	17.6	18.3	19.3
Consumer loans to total loans	9.5	9.9	10.0	9.8	10.4	10.9
Mortgage loans to total loans	6.8	6.8	6.8	6.7	6.9	7.6
Loans to households as employers to total loans	1.1	1.1	1.1	1.1	0.9	0.8

Source: Philippines authorities; IMF, *Financial Soundness Indicators*; and IMF staff estimates.

*As of September 2020.

Source: IMF (2021).

Annex IV. Philippines Selected Economic Indicators, 2016-21

Demographic: Population (2020): 108.8 million; Life expectancy at birth (2018): 71

Poverty (2015, percent of population): Below \$1.90 a day: 6.1; Below the national poverty line: 21.6

Inequality (2015, income shares): Top 10 percent: 34.8; Bottom 20 percent: 5.7

Business environment (2019 country ranking): Ease of doing business: 95 (out of 190); Starting a business: 171 (out of 190)

IMF quota: SDR 2,042.9 million

Main products and exports: electronics, agriculture products, and business process outsourcing

	2016	2017	2018	2019	2020 Proj.	2021 Proj.
(Annual percentage change, unless otherwise indicated)						
National account						
Real GDP	7.1	6.9	6.3	6.0	-9.6	6.6
Consumption	7.4	6.0	6.8	6.4	-4.9	7.7
Private	7.1	6.0	5.8	5.9	-7.4	7.3
Public	9.4	6.5	13.4	9.6	9.6	9.2
Gross fixed capital formation	20.9	10.6	12.9	3.9	-27.9	8.2
Domestic demand	10.2	7.1	8.2	5.8	-10.4	7.8
Net exports (contribution to growth)	-3.8	-0.9	-2.3	-0.1	3.6	-2.4
Real GDP per capita	5.4	5.2	4.7	4.5	-10.9	5.0
Output gap (percent, +=above potential)	0.1	0.4	0.2	-0.1	-2.4	-0.5
Labor market						
Unemployment rate (percent of labor force)	5.5	5.7	5.3	5.1	10.4	7.4
Underemployment rate (percent of employed persons)	18.3	16.1	16.4	13.8	16.2	...
Employment (percent change)	4.7	-1.6	2.0	1.9	-6.1	5.2
Non-agriculture daily wages (Q4/Q4) 1/	2.1	4.3	4.9	0.0
Price						
Consumer prices (period average, 2012 basket)	1.3	2.9	5.2	2.5	2.6	3.2
Consumer prices (end of period, 2012 basket)	2.2	2.9	5.1	2.5	3.5	3.1
Core consumer prices (period average, 2012 basket)	1.5	2.5	4.1	3.2	3.1	...
Residential real estate (Q4/Q4) 2/	3.3	5.7	0.6	10.2
Money and credit						
3-month PHIREF rate (percent, end of period) 3/	2.0	3.3	6.5	3.1	1.3	...
Claims on private sector (percent of GDP)	42.9	45.6	47.6	48.0	53.7	52.9
Claims on private sector (percent change)	16.6	16.4	15.1	7.8	3.1	8.7
Public finances (in percent of GDP)						
National government overall balance 4/	-2.3	-2.1	-3.1	-3.4	-7.7	-9.1
Revenue and grants	14.5	14.9	15.5	16.1	15.9	14.5
Total expenditure and net lending	16.8	17.1	18.7	19.5	23.5	23.6
General government gross debt	37.3	38.1	37.1	37.0	47.0	52.3
Balance of payments (in percent of GDP)						
Current account balance	-0.4	-0.7	-2.6	-0.9	2.6	-1.2
FDI, net	-1.8	-2.1	-1.7	-1.2	-1.6	-1.0
Gross reserves (US\$ billions)	80.7	81.6	79.2	87.8	109.8	109.0
Gross reserves (percent of short-term debt, remaining maturity)	418.2	419.3	369.0	387.0	440.9	418.0
Total external debt	23.5	22.3	22.8	22.2	25.4	24.8
Memorandum items:						
Nominal GDP (US\$ billions)	318.6	328.5	346.8	376.8	362.7	391.7
Nominal GDP per capita (US\$)	3,108	3,153	3,280	3,512	3,334	3,547
GDP (in billions of pesos)	15,132	16,557	18,265	19,516	17,997	19,860
Real effective exchange rate (2005=100)	108.2	103.4	100.5	105.3
Peso per U.S. dollar (period average)	47.5	50.4	52.7	51.8	49.6	...

Sources: Philippine authorities; World Bank; and IMF staff estimates and projections.

1/ In National Capital Region.

2/ Latest observation as of 2019:Q4.

3/ Benchmark rate for the peso floating leg of a 3-month interest rate swap.

4/ IMF definition. Excludes privatization receipts and includes deficit from restructuring of the previous Central Bank-Board of Liquidators.

Source: IMF (2021).

References

- AIR Worldwide, 2017. [Climate Change Impacts on Extreme Weather](#), White Paper.
- Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA), 2018. Observed and Projected Climate Change in the Philippines. Philippine Atmospheric, Geophysical, and Astronomical Services Administration, Quezon City, Philippines.
- Autorité de contrôle prudentiel et de résolution (ACPR), 2021. [A first assessment of financial risks stemming from climate change](#): The main results of the 2020 climate pilot exercise. ACPR Analyses et Synthèses No. 122-2021.
- Aznar-Siguan, G., Eberenz, S., Steinmann, C., Vogt, T., Roosli, T., Sauer, I., and Zhu, Q. 2021. CLIMADA-project/climada_python_v2.1.1 (Version v2.1.1.). Zenodo.
- Bank of England (BoE), 2019. [The 2021 biennial exploratory scenario on the financial risks from climate change](#).
- Bank of Canada (BoC) and Office of the Superintendent of Financial Institutions (OSFI), 2022. [Using Scenario Analysis to Assess Climate Transition Risk](#). Final Report of the BOC-OSFI Climate Scenario Analysis Pilot.
- Batten, S., Sowerbutts, R., & Tanaka, M., 2016. Let's Talk About the Weather: The Impact of Climate Change on Central Banks. [Bank of England Working Paper, No. 603](#).
- Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., and Visentin, G., 2017, A climate stress-test of the financial system. *Nature Climate Change*, 7(4), 283–288.
- Campiglio, E., Dafermos, Y., Monnin, P., Ryan-Collins, J., Schotten, G., and Tanaka, M., 2018, Climate change challenges for central banks and financial regulators. *Nature Climate Change*, 8(6), 1–13.
- Christiano, L.J., Motto, R. and Rostagno, M., 2014. Risk shocks. *American Economic Review*, 104(1), pp.27-65.
- Climate Action Tracker, 2021. <https://climateactiontracker.org/global/temperatures/> (May).
- De Nederlandsche Bank (DNB), 2017. [Waterproof?](#) An exploration of climate-related risks for the Dutch financial sector.
- _____, 2019. [An energy transition risk stress test for the financial system of the Netherlands](#), Occasional Studies Volume 16-7.
- Deryugina, T., Kawano, L., and Levitt, S., 2018. The economic impact of Hurricane Katrina on its victims: evidence from individual tax returns. *American Economic Journal: Applied Economics*, 10(2), 202-33.

- Dieppe, A., Kilic Celik, S., and Okou, C. (2020). Implications of major adverse events on productivity. Working Paper 9411, The World Bank
- Dunz, N., Essenfelder, A.H., Mazzocchetti, A., Monasterolo, I. and Raberto, M., 2021. Compounding COVID-19 and climate risks: the interplay of banks' lending and government's policy in the shock recovery. *Journal of Banking & Finance*, p.106306.
- European Banking Authority (EBA), 2021. [Mapping climate risk](#): Main findings from the EU-wide pilot exercise. EBA/Rep/2021/11.
- European Central Bank (ECB), 2021, [ECB economy-wide climate stress test](#), Methodology and results, ECB Occasional Paper Series, No. 281.
- Feyen, E.H., Utz, R.J., Zuccardi Huertas, I.E., Bogdan, O., and Moon, J., 2020, Macro-Financial Aspects of Climate Change. World Bank Policy Research Working Paper (9109).
- Financial Stability Institute (FSI), 2021. [Stress-Testing banks for climate change—a comparison of practices](#), by P. Baudino and J. Svoronos, FSI Insights on Policy Implementation, No. 34.
- Gallo, F., Daron, J., Macadam, I., Cinco, T., Villafuerte II, M., Buonomo, E., Tucker, S., Hein-Griggs, D., and Jones, R., 2018. High-resolution regional climate model projections of future tropical cyclone activity in the Philippines, [International Journal of Climatology, Vol. 39, Issue 3](#).
- Good, P., Lowe, J., Ridley, J., Bamber, J., Payne, T., Keen, A., Stroeve, J., Jackson, L., Srokosz, M., Kay, G., Harper, A., Kruijt, B., Burke, E., Abbott, B., O'Connor, F., Minshull, T., Turley, C. and Williamson, P., 2014. An updated view of tipping points and the relevance for long-term climate goals.
- Golnaraghi, 2021. Climate Change Risk Assessment for the Insurance Industry—Research Report. The Geneva Association.
- Grippa, P., and Mann, A., 2020. Climate-Related Stress Testing: Transition Risks in Norway. [IMF Working Paper No. 2020/232](#).
- Groen, J.A., and Polivka, A.E., 2008. The effect of Hurricane Katrina on the labor market outcomes of evacuees. *American Economic Review*, 98(2), 43-48.
- Hallegatte, S., and Vogt-Schilb, A., 2019. Are losses from natural disasters more than just asset losses? The role of capital aggregation, sector interactions, and investment behaviors, In: Okuyama Y., Rose A. (eds) *Advances in Spatial and Economic Modeling of Disaster Impacts*. Advances in Spatial Science (The Regional Science Series). Springer, Cham. https://doi.org/10.1007/978-3-030-16237-5_2
- Hallegatte, S., Jooste, C., and McIsaac, F., 2022. Macroeconomic Consequences of Natural Disasters: A Modeling Proposal and Application to Floods and Earthquakes in Turkey. Policy Research working paper, no. WPS 9943 Washington, D.C. : World Bank Group.

Hansen, L.P., 2021. Central Banking Challenges Posed by Uncertain Climate Change and Natural Disasters. Becker Friedman Institute Working Paper No. 2021-64.

International Monetary Fund (IMF), 2017. *World Economic Outlook*, October 2017. Chapter 3: The Effects of Weather Shocks on Economic Activity: How Can Low-Income Countries Cope?

_____, 2019. [The Bahamas: Financial Sector Assessment Program—Technical Note on Financial Stability and Stress Testing](#).

_____, 2020. [Financial System Stability Assessment for Norway](#).

_____, 2021a. [Financial System Stability Assessment for the Philippines](#).

_____, 2021b. [2021 Financial Sector Assessment Program \(FSAP\) Review—Towards a more stable and sustainable financial system](#).

_____, 2021c. 2021 FSAP Review—[Background Paper on Quantitative Analysis](#).

_____, 2021d. 2021 FSAP Review—[Background Paper on Scope](#).

_____, 2022. [Financial System Stability Assessment for the United Kingdom](#).

_____, (forthcoming). 2021 Philippines FSAP: Technical Note on Risk Assessment of Banks, Non-Financial Corporates, and Macro-Financial Linkages.

Intergovernmental Panel on Climate Change (IPCC), 2013. Summary for Policymakers. In: *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley, P.M., eds.). Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA

_____, 2014. *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (Barros, V.R., Field, C.B., Dokken, D.J., Mastrandrea, M.D., Mach, K.J., Bilir, T.E., Chatterjee, M., Ebi, K.L., Estrada, Y.O., Genova, R.C., Girma, B., Kissel, E.S., Levy, A.N., MacCracken, S., Mastrandrea, P.R., and White, L.L., eds.). Cambridge University Press, Cambridge United Kingdom and New York, NY, USA, 688.

_____, 2021. Weather and Climate Extreme Events in a Changing Climate. In *Climate Change 2022: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, [full report](#) and [summary for policymakers](#).

Jung, H., R. Engle, R. Berner, 2021. [Climate Stress Testing](#). Federal Reserve Bank of New York Staff Reports, No. 977.

- Knutson, T., Camargo, S.J., Chan, J.C.L., Emanuel, K., Ho C., Kossin, J., Mohapatra M., Satoh, M., Sugi, M., Walsh, K., and Wu, L., 2020. Tropical Cyclones and Climate Change Assessment. [Part II: Projected Response to Anthropogenic Warming](#). Bulletin of the American Meteorological Society.
- Knutson, T.R., Sirutis, J.J., Zhao, M., Tuleya, R.E., Bender, M., Vecchi, G.A., Villarini, G., and Chavas, D., 2015. Global projections of intense tropical cyclone activity for the late twenty-first century from dynamical downscaling of CMIP5/RCP4. 5 scenarios. *Journal of Climate*, 28(18), 7203-24.
- Leaton, J., Ranger, N., Ward, R., Sussams, L., and Brown, M., 2013. Unburnable Carbon 2013—Wasted Capital and Stranded Assets. Carbon Tracker Initiative and London School of Economics and Political Science.
- Lempert, R.J., Popper, S., and Bankes, S., 2003, Shaping the next one hundred years: new methods for quantitative, long-term policy analysis. [Rand Corporation](#).
- Lempert, R.J., Popper, S.W., Groves, D.G., Kalra, N., Fischbach, J.R., Bankes, S.C., Bryant, B.P., Collins, M.T., Keller, K., Hackbarth, A., and Dixon, L., 2013. Making good decisions without predictions: Robust decision making for planning under deep uncertainty. [RAND Corporation Research Brief](#).
- Lipinsky, F., and Miescu, M.S., 2020. *Capital Gaps, Risk Dynamics, and the Macroeconomy*. IMF Working Paper No. 2020/209.
- Lloyd's, 2014. [Catastrophe modelling and climate change](#).
- Millner, A., Dietz, S., and Heal, G., 2013. Scientific ambiguity and climate policy. *Environmental and Resource Economics*, 55(1), 21-46.
- Monasterolo, I., Billio, M. and Battiston, S., 2020. The importance of compound risk in the nexus of COVID-19, climate change and finance. *Climate Change and Finance (June 20, 2020)*.
- Nelson, G., H. Valin, R., Sands, P., Havlick, H., Ahammad, D., Derynge, J., Elliott, S., Fujimori, T., Hasegawa, E., Heyhoe, P., Kyle, M., Von Lampe, H., Lotze-Campen, D., d'Croz, H., van Meijl, D., van der Mensbrugghe, C., Müller, A., Popp, R., Robertson, S., Robinson, E., Schmid, C., Schmitz, A., Tabeau, and D. Willenbockel, 2014. Climate change effects on agriculture: economic responses to biophysical shocks, Proceedings of the National Academy of Sciences of the U.S.A. (PNAS), Vol. 11, No. 9.
- Network of Central Banks and Supervisors Greening Financial System (NGFS), 2020a. [Guide to climate scenario analysis for central banks and supervisors](#).
- _____, 2020b. [The macroeconomic and financial stability impacts of climate change: research priorities](#).
- _____, 2021a. [NGFS Climate Scenarios for central banks and supervisors](#), June 2021.
- _____, 2021b. [Scenarios in Action](#): A progress report on global supervisory and central bank climate scenario exercises.
- _____, 2021c. [Progress report on bridging data gaps](#), May 2021.

- Ranger and Niehörster, 2012. Deep uncertainty in long-term hurricane risk: Scenario generation and implications for future climate experiments. *Global Environmental Change* Volume 22, Issue 3, August 2012, 703-12.
- Reinders, H.J., Schoenmaker, D., and van Dijk, M., 2020. A finance approach to climate stress testing. CEPR Discussion Paper.
- Rogelj, J., Popp, A., Calvin, K.V, Luderer, G., Emmerling, J., Gernaat, D., Fujimori, S., Streffer, J., Hasegawa, T., and Marangoni, G., 2018. Scenarios towards limiting global mean temperature increase below 1.5 C. *Nature Climate Change*, 8(4), 325.
- Smale, R., Hartley, M., Hepburn, C., Ward, J., and Grubb, M., 2006, The impact of CO2 emissions trading on firm profits and market prices. *Climate Policy*, 6(1), 31–48.
- Task Force on Climate-related Financial Disclosures (TCFD), 2021. [2021 Status Report](#).
- United Nations Environmental Program (UNEP), 2020. [Emissions Gap Report 2020](#). Nairobi.
- _____, —Acclimatise, 2018. [Navigating a New Climate: Assessing credit risk and opportunity in a changing climate. Part 2](#): Physical risks and opportunities.
- _____, —Oliver Wyman, 2018. [Extending Out Horizons: Assessing credit risk and opportunity in a changing climate. Part 1](#): Transition-related risks and opportunities.
- Vermeulen, R., Schets, E., Lohuis, M., Kölbl, B., and Jansen, D., 2019. The Heat is on : A framework measuring financial stress under disruptive energy transition scenarios. DNB Working Paper 625.
- Vigdor, J., 2008. The economic aftermath of Hurricane Katrina. *Journal of Economic Perspectives*, 22(4), 135-54.



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