
Methods

To estimate the impact of climate change on the economy, it is necessary to compare a scenario in which the economy evolves as if climate was stable and a scenario in which the economy evolves in response to a changing climate. As it is impossible to observe how the economy evolves under two different climates, researchers build scenarios using different methods. Impacts can vary depending on how much adaptation is assumed to occur as a response to climate change. Some models allow for no or very minimal adaptation, whereas other models deploy a wide range of responses. Comparison of results across studies is complicated because models used in the literature differ in how much adaptation to include in their estimates of climate change damages. To estimate the economic benefit of adaptation, models must incorporate adaptation mechanisms that can be turned on and off to generate scenarios with and without adaptation. The benefit of such adaptation can then be measured by comparing economic losses under climate change with and without adaptation. Not all models have this degree of flexibility to study climate change impacts and adaptation. Some methods can be used to estimate climate change damages without or with minimal adaptation. Other methods can be used to estimate the impact of climate change with adaptation, but they are “black boxes” where the adaptation mechanisms cannot be easily controlled. This annex provides a synthetic overview of the main methods to study climate change impacts and adaptation. For much more detailed recent reviews of the literature see Kahn (2016), Auffhammer (2018), Massetti and Mendelsohn (2018), Tol (2018), and papers in the special issue edited by Fisher-Vanden, Popp, and Sue Wing (2014).

It is possible to separate the methods used in the literature to estimate climate change impacts and adaptation in two broad groups. The first group relies on the parameterization of models that can simulate the economy or other sectoral outcomes (for example, crop yields, energy and water demand) as a function of exogenous variables and model parameters. These can be called “simulation models” because they can simulate how the exogenous variables (GDP, yields, etc.) evolve under different choices of exogenous variables, including climate. Simulation models can be very complex and computationally intensive. The second group relies on econometric methods to estimate reduced form functions of how climate affects the economy or other variables of interest. Econometric models have a much lower level of detail of simulation models but also avoid many ad hoc assumptions that are needed in large simulation models.

Simulation Models

Simulation models have been extensively used to estimate both the benefit and costs of adaptation. These types of studies cover sectoral models without optimizing agents, like engineering models (used to study water management systems or sea-level rise protection) (Hurd and others 2004; Lund, Cai, and Characklis 2006; Nicholls and Tol 2006; Yohe and others 1996; Hallegatte and others 2013; Diaz 2015), forestry models (to study optimal tree selection, rotation, and management) (Sohngen and Mendelsohn 1998; Sohngen, Mendelsohn, and Sedjo 2001), or agriculture models (used to identify optimal management and crop selection) (Tubiello and Fischer 2007; Blanc and Reilly 2017; Reilly and others 2003). They also include partial equilibrium and GE models with optimizing agents where adaptation is chosen efficiently and allowing for the study of autonomous adaptation, including through
trade and factor reallocation (Bosello, Carraro, and De Cian 2013; Bosello, Roson, and Tol 2006; Costinot, Donaldson, and Smith 2016). The advantage of simulation studies is that they can measure the effect of different adaptation solutions by turning them on and off in various simulations. They can also simulate the impact of climates that have not been experienced yet. For this reason, they have been used extensively to study virtually all climate-sensitive sectors, with protection from sea-level rise as a primary application. These studies provide explicit estimates of adaptation investment needs and residual damage. The disadvantage of these models is that they rely on many assumptions on behavior, technology, and costs that make them very sensitive to alternative parameterizations.

Two special classes of simulation methods are Integrated Assessment Models and Computable General Equilibrium Models.

- **Integrated Assessment Models (IAMs)** integrate the energy system, the economy, the climate system, and in some cases land, in a single framework. The models used for studies surveyed in Figure 1 are DICE and its regional variant RICE (Nordhaus 1992, 1993; Nordhaus and Boyer 2000), FUND (Tol 1997, 2018), and PAGE (Plambeck and Hope 2006). Other IAMs used for cost-benefit assessment of climate mitigation are MERGE (Manne, Mendelsohn, and Richels 1995) and WITCH (Bosetti et al. 2006, 2007, 2013). This is a small set of models. Many energy-economy models that are also commonly called IAMs do not describe the feedback of the climate system on the economy and are used to study climate mitigation policy without estimating mitigation benefits (Weyant 2017).

IAMs are primarily concerned with long-term dynamics of capital accumulation, investment in the energy sector, and climate change. Few sectors of the economy are modeled in detail. Countries are aggregated in macro-regions or in a single global region. These modes calibrate a macroeconomic damage function that relates global GDP and temperature starting from sectoral and regional studies, including evidence from econometric studies. Impacts are estimated assuming different levels of adaptation, which can be efficient in some models or inefficient in others. The cost of private adaptations is not always included in IAMs, which overestimates the benefit of adaptation. Technological progress in adaptation (for example, better heat- and drought-resistant crops or more efficient protections against sea-level rise) is also not always included in IAMs, which underestimates the potential benefit of adaptation. The net effect is uncertain because these biases have opposite effects.

Although there are differences across IAMs, a wide range of impacts is considered: temperature change, sea-level rise, tropical cyclones, and catastrophic events. In some cases, nonmarket losses (for example, losses from ecosystems and amenity values) are monetized and included among damages.

Several authors have criticized the use of IAMs, especially their use in cost-benefit analysis of climate mitigation policy. One recurring theme is the inability to model catastrophic climate outcomes (for example, Pindyck 2013). While in many cases IAMs include extreme impacts and catastrophic events in their damage functions, the models do not include dynamics that can lead to societal collapses.

- **Computable general equilibrium models (CGEs)** include many sectors and many regions, with trade among regions and sectors. This greater sectoral and geographic detail can usually be accommodated by shortening the simulation horizon relative to IAMs. The long-term dynamic
relationship between the economy and climate cannot be reproduced with the same detail of IAMs. These models rely on exogenous climate shocks and are parameterized using econometric evidence.

CGEs can provide many useful insights on aggregate climate change impacts and on market adaptations, with the possibility to estimate how each channel (for example, international trade) contributes to reducing (or amplifying) climate change impacts. Dynamic Stochastic General Equilibrium (DSGE) models reviewed in the main text of this Note also belong to this class but have not yet been applied to estimate global climate change costs.

**Econometric Methods**

**Econometric models based on cross-sectional analysis** are used to estimate climate change impacts at both sectoral and macroeconomic levels and to identify climate adaptations (Mendelsohn, Nordhaus, and Shaw 1994; Schlenker, Haneman, and Fisher 2005; Nordhaus 2006; Kalkuhl and Wenz 2020). A reduced form equation in which economic variables (for example, GDP per capita, agricultural rents), or sectoral output (for example, crop yields, water use), are a function of climate and control variables is estimated using cross-sectional variation. The estimated climate coefficients are used to predict the effect of climate change on the dependent variable. This method allows including present-day adaptation. Impacts are estimated using the climate coefficients estimated with the cross-sectional analysis with climate variables as expected in the future. These models assume that the same kinds of adaptations that are observed across climates today will spread following climate change. Cross-sectional studies are also used to identify climate adaptations by comparing what people do in different climates. There is evidence that climate affects consumption and both private and public investment in climate sensitive sectors like agriculture, energy, recreation, tourism, and investment in resilience to extreme events (Massetti and Mendelsohn 2018). However, this literature does not generally provide estimates of the economic benefit of adaptation. The advantage of cross-sectional econometric models is that they rely on observed behavior and project future adaptations from what individuals and governments do to respond to a wide range of climates. The main challenge for these studies is to control for confounding variables, such as geographic and socioeconomic characteristics that are correlated with both climate and the adaptation studied (Deschênes and Greenstone 2012; Blanc and Schlenker 2017).

**Econometric models based on panel analysis** identify the effect of weather shocks on changes of GDP per capita, using either fixed effects or first differences. Impacts of warming are projected using short-term elasticities, without accounting for adaptation that relies on stocks. To identify the effect of weather, these methods focus their attention on the impact of unexpected shocks over short periods of time and are therefore unable to capture adaptation benefits that take time to unfold (Mendelsohn and Massetti 2017; Lemoine 2018; Massetti and Mendelsohn 2018; Tol 2018; Letta and Tol 2019; Kolstad and Moore 2020). The slow adjustment of capital makes impacts from unexpected deviations of weather from normal conditions different from slow-moving climate change. Inferring climate change impacts from unexpected shocks implies that the short-term imperfections are permanent. For example, as heat extremes become more frequent, we may see more increased mortality from heat stress in households in areas where mild temperatures have not stimulated the adoption of air conditioning, but as it becomes clear that the temperature distribution has shifted, it is reasonable to expect that air conditioning will be adopted and mortality will converge to that in areas that today already have air conditioning. Projecting mortality at the end of the century using elasticities estimated using weather shocks implies that air conditioning—or any other adaptation—will never be adopted over the next 80 years.
For this reason, this literature is generally not used to estimate the economic benefit of adaptation, with some exceptions. Some studies compare the effect of weather shocks in different climates or over time to learn if weather shocks have different impacts in different climates, a result that can be interpreted as evidence of adaptation (Schlenker and Roberts 2009; Deschênes and Greenstone 2011; Burke and Emerick 2016). Kahn and others (2021) measure weather shocks relative to a trailing moving average of weather. With this method, the authors estimate that adaptation has the potential to halve the long-term cost of warming.

**Estimates of Climate Change Damages**

Figure 1 in the main text displays estimates of global climate change damages from a comprehensive review of the literature. The full list of studies is available in Annex Table 1.1. Studies that estimate regional costs as well as studies that estimate climate change damages using the metric of the social cost of carbon are not included because they are not easily comparable with the others.

**Estimating the cost of climate change is a complex exercise with many sources of uncertainty.** The estimates reported in Figure 1 reveal that damages from global warming in the range of +1.5°C to +2.5°C (approximately SSP1–2.6) could lead to a median loss of 1.5 percent [–13.0, +0.1] of annual global GDP in 2100, with respect to its reference level without climate change (ranges are in brackets). With +2.9°C to +4.3°C of global warming (approximately SSP3–7.0), the median predicted loss increases to 3.3 percent [–23, –0.8] of GDP in 2100 (see Figure 1). These ranges reflect the status of the literature but do not span all possible future outcomes because of the inherent limitations of studies.

How is it possible to reconcile estimated average costs that can seem rather small with the large concern expressed by scientists and the international community? The answer is that these studies may substantially underestimate the global cost of climate change in several ways and that global averages do not reveal the unequal distribution of climate change impacts, which imply devastating impact for some small vulnerable countries:

- The costs presented in Figure 1 are global averages that hide large negative effects in developing countries that are already hot, in small vulnerable nations, as shown in the academic literature (Mendelsohn, Dinar, and Williams 2006; Dell, Jones, and Olken 2012) and in several recent IMF studies (IMF 2018, 2020b, 2021d, 2021f). Some small island developing states are at risk of disappearing due to sea-level rise (World Bank 2017). However, by being small and often poor, very large loss-to-GDP ratios in these countries do not contribute significantly to global damages (IMF 2021f). Global average costs are also attenuated by potential gains in some colder countries in some studies (Burke, Hsiang, and Miguel 2015; Kalkuhl and Wenz 2020). Within countries, disadvantaged sectors of the population will suffer larger welfare losses. These uneven effects of climate change are of great concern for economic and ethical reasons and because they could push some countries to unsustainable fiscal territory and may lead to global macro instability.

- Some studies that use IAMs include damages from only some climate catastrophes and losses enter as expected values (Nordhaus and Boyer 2000; Stern 2007). Econometric studies only consider temperature and sometimes precipitation (Burke, Hsiang, and Miguel 2015; Dell, Jones, and Olken 2012). This means that worst-case scenarios are missing from Figure 1. Some studies that we do not include in our review because they cannot be easily compared simulate the cost of crossing “tipping points” and find that damages can be substantially large, but there is large
uncertainty in the literature (Cai, Lenton, and Lontzek 2016; Nordhaus 2019; Dietz and others 2021). The existence of low-probability but high-negative impact events that cannot be easily quantified (Weitzman 2011) is the one of the main factors behind the declared intention to keep global warming below +2.0°C and possibly +1.5°C.

- Nonmarket impacts (for example, biodiversity loss and loss of desirable climatic conditions) are also imperfectly included by some of the IAMs, as these estimates are uncertain and hard to quantify. The future value of nonmarket irreplaceable goods may be underestimated (Sterner and Persson 2020; Hoel and Sterner 2007).

- None of the studies surveyed in Figure 1 consider the possibility of crossing societal tipping points triggered by climate change (for example, social conflicts, wars, disruptive migration flows) because empirical data to quantify these risks is lacking.

- Finally, GDP only measures economic output and is at best a partial measure of welfare. It does not reflect the welfare losses resulting from channeling more resources for investment away from consumption (as would be needed if post-disaster reconstruction needs become more frequent). GDP losses also underestimate welfare losses when consumption losses are concentrated on certain groups, on poorer people as is expected with climate change (Hallegatte and others 2016a).

### Annex Table 1.1. Survey of the Literature on the Economic Costs of Climate Change

<table>
<thead>
<tr>
<th>Author</th>
<th>Temperature Change (degree Celsius)</th>
<th>Global GDP Loss (percentage)</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Integrated Assessment Models</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tol (2013)</td>
<td>1.0</td>
<td>−1.4</td>
<td>Calculated using DICE2016R-090916ap-v2, which was used by Nordhaus (2017)</td>
</tr>
<tr>
<td>Nordhaus (2017)</td>
<td>1.0</td>
<td>−0.2</td>
<td></td>
</tr>
<tr>
<td>Gunasekera and others (2008)</td>
<td>1.7</td>
<td>−1.4</td>
<td>The study uses +1.3°C with respect to temperature in 2000; adjusted by adding 0.4°C</td>
</tr>
<tr>
<td>Hope (2006)</td>
<td>2.5</td>
<td>−0.9</td>
<td></td>
</tr>
<tr>
<td>Manne and Richels (2005)</td>
<td>2.5</td>
<td>−1.9</td>
<td></td>
</tr>
<tr>
<td>Manne, Mendelsohn and Richels (1995)</td>
<td>2.5</td>
<td>−1.4</td>
<td></td>
</tr>
<tr>
<td>Nordhaus (2017)</td>
<td>2.5</td>
<td>−1.5</td>
<td>Calculated using DICE2016R-090916ap-v2, which was used by Nordhaus (2017)</td>
</tr>
<tr>
<td>Nordhaus and Boyer (2000)</td>
<td>2.5</td>
<td>−1.5</td>
<td></td>
</tr>
<tr>
<td>Nordhaus and Yang (1996)</td>
<td>2.5</td>
<td>−1.7</td>
<td></td>
</tr>
<tr>
<td>Plambeck and Hope (1996)</td>
<td>2.5</td>
<td>−2.5</td>
<td></td>
</tr>
<tr>
<td>Tol (1995)</td>
<td>2.5</td>
<td>−1.9</td>
<td></td>
</tr>
</tbody>
</table>

*Continued*
<table>
<thead>
<tr>
<th>Author</th>
<th>Temperature Change (degree Celsius)</th>
<th>Global GDP Loss (percentage)</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Integrated Assessment Models (continued)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nordhaus (2013)</td>
<td>2.9</td>
<td>−2.0</td>
<td></td>
</tr>
<tr>
<td>Hope (2011)</td>
<td>3.0</td>
<td>−0.8</td>
<td></td>
</tr>
<tr>
<td>Nordhaus (2014)</td>
<td>3.0</td>
<td>−10.6</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.0</td>
<td>−4.9</td>
<td></td>
</tr>
<tr>
<td>Nordhaus (2017)</td>
<td>3.0</td>
<td>−2.2</td>
<td>Calculated using DICE2016R-090916ap-v2, which was used by Nordhaus (2017)</td>
</tr>
<tr>
<td>Nordhaus (1994a)</td>
<td>3.0</td>
<td>−3.6</td>
<td></td>
</tr>
<tr>
<td>Nordhaus (1994b)</td>
<td>3.0</td>
<td>−1.3</td>
<td></td>
</tr>
<tr>
<td>Nordhaus (2008)</td>
<td>3.0</td>
<td>−2.5</td>
<td></td>
</tr>
<tr>
<td>Gunasekera and others (2008)</td>
<td>3.8</td>
<td>−11.4</td>
<td>The study uses +1.3°C with respect to temperature in 2000; adjusted by adding 0.4°C</td>
</tr>
<tr>
<td>Stern (2007)</td>
<td>3.9</td>
<td>−0.9</td>
<td>Includes market impacts and catastrophes</td>
</tr>
<tr>
<td>Nordhaus (2017)</td>
<td>4.3</td>
<td>−4.4</td>
<td>Calculated using DICE2016R-090916ap-v2, which was used by Nordhaus (2017)</td>
</tr>
<tr>
<td>Stern (2007)</td>
<td>4.3</td>
<td>−2.9</td>
<td>Includes market impacts and catastrophes</td>
</tr>
<tr>
<td><strong>Cross Section Econometrics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Horowitz (2009)</td>
<td>1.0</td>
<td>−3.8</td>
<td></td>
</tr>
<tr>
<td>Choinière and Horowitz (2000)</td>
<td>1.1</td>
<td>−7.4</td>
<td></td>
</tr>
<tr>
<td>Horowitz (2009)</td>
<td>2.0</td>
<td>−7.6</td>
<td>Linearly extrapolated from impact of 1°C as the study finds impacts are almost linear</td>
</tr>
<tr>
<td>Mendelsohn and others (2000)</td>
<td>2.5</td>
<td>+0.1</td>
<td></td>
</tr>
<tr>
<td>Nordhaus (2006)</td>
<td>3.0</td>
<td>−0.9</td>
<td>Only warming; output weights</td>
</tr>
<tr>
<td></td>
<td>3.0</td>
<td>−1.1</td>
<td>Warming and drying; output weights</td>
</tr>
<tr>
<td></td>
<td>3.0</td>
<td>−1.7</td>
<td>Only warming; population weights</td>
</tr>
<tr>
<td></td>
<td>3.0</td>
<td>−3.0</td>
<td>Warming and drying; population weights</td>
</tr>
<tr>
<td>Kalkuhl and Wenz (2020)</td>
<td>3.5</td>
<td>−6.6</td>
<td></td>
</tr>
<tr>
<td><strong>Panel Econometrics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pretis and others (2018)</td>
<td>1.5</td>
<td>−8.0</td>
<td></td>
</tr>
<tr>
<td>Kahn and others (2021)</td>
<td>1.6</td>
<td>−0.6</td>
<td>Fast adaptation</td>
</tr>
<tr>
<td></td>
<td>1.6</td>
<td>−1.6</td>
<td>Medium adaptation</td>
</tr>
<tr>
<td></td>
<td>1.6</td>
<td>−1.1</td>
<td>Slow adaptation</td>
</tr>
<tr>
<td>Author</td>
<td>Temperature Change (degree Celsius)</td>
<td>Global GDP Loss (percentage)</td>
<td>Notes</td>
</tr>
<tr>
<td>---------------------------------------------</td>
<td>------------------------------------</td>
<td>-----------------------------</td>
<td>---------------------</td>
</tr>
<tr>
<td>Pretis and others (2018)</td>
<td>2.0</td>
<td>−13.0</td>
<td></td>
</tr>
<tr>
<td>Kalkuhl and Wenz (2020)</td>
<td>3.5</td>
<td>−11.4</td>
<td></td>
</tr>
<tr>
<td>Burke, Hsiang, and Miguel (2015)</td>
<td>4.3</td>
<td>−23.0</td>
<td></td>
</tr>
<tr>
<td>Kahn and others (2021)</td>
<td>4.3</td>
<td>−4.4</td>
<td>Fast adaptation</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>−10.0</td>
<td>Medium adaptation</td>
</tr>
<tr>
<td></td>
<td></td>
<td>−7.2</td>
<td>Slow adaptation</td>
</tr>
</tbody>
</table>

Panel Econometrics (continued)

<table>
<thead>
<tr>
<th>Author</th>
<th>Temperature Change (degree Celsius)</th>
<th>Global GDP Loss (percentage)</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bosello and others (2012)</td>
<td>1.9</td>
<td>−0.5</td>
<td></td>
</tr>
<tr>
<td>Dellink and others (2014)</td>
<td>2.5</td>
<td>−1.1</td>
<td></td>
</tr>
<tr>
<td>Roson and Van der Mensbrugghe (2012)</td>
<td>2.9</td>
<td>−1.8</td>
<td></td>
</tr>
</tbody>
</table>

Computable General Equilibrium Models

<table>
<thead>
<tr>
<th>Author</th>
<th>Temperature Change (degree Celsius)</th>
<th>Global GDP Loss (percentage)</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tol (2002)</td>
<td>1.0</td>
<td>−2.7</td>
<td>Aggregation from sectoral studies; globally averaged prices for nonmarket goods</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.0</td>
<td>+0.2</td>
<td>Aggregation from sectoral studies; equity weights</td>
</tr>
<tr>
<td></td>
<td>1.0</td>
<td>+2.3</td>
<td>Aggregation from sectoral studies; simple aggregation</td>
</tr>
<tr>
<td>Fankhauser (1995)</td>
<td>2.5</td>
<td>−1.4</td>
<td>Aggregation from sectoral studies.</td>
</tr>
<tr>
<td>Schauer (1995)</td>
<td></td>
<td>−5.2</td>
<td>Expert elicitation</td>
</tr>
<tr>
<td>Nordhaus (1994a)</td>
<td>3.0</td>
<td>−1.9</td>
<td>Expert elicitation</td>
</tr>
<tr>
<td>Howard and Sylvan (2015)</td>
<td>3.0</td>
<td>−5.0</td>
<td>Expert elicitation; median response of economists</td>
</tr>
<tr>
<td></td>
<td>3.0</td>
<td>−7.1</td>
<td>Expert elicitation; mean response of economists</td>
</tr>
</tbody>
</table>

Other Methods

Source: Staff elaboration compiled from surveys in Tol (2009, 2014), Kahn et al. (2021), and Howard and Sterner (2017).
Note: Several studies in previous surveys have not been included if (1) they were not published in peer-reviewed journals and with 10 or fewer citations in Google Scholar at the time of writing; (2) they measure the impact on life satisfaction, utility, or happiness; (3) they lack estimates of global impacts; and (4) global mean surface temperature change with respect to the pre-industrial level is greater than 5°C.
Annex 2. The Costs of Making Infrastructure More Resilient

The current climate is already a source of risks for physical infrastructure that should be addressed. While many important and necessary adaptation policies are needed (strengthening early warning systems, agriculture systems, and water resources management), investing in infrastructure resilience is the costliest (GCA 2018). Vulnerabilities to floods and storms have been estimated to be the costliest source of climate risks in the present (Centre for Research on the Epidemiology of Disasters n.d.) and into the future (Lange and others 2020). However, starting by addressing the existing vulnerabilities is the most practical step forward. Hence, we focus on the cost of strengthening existing exposed economic assets and investment projects to improve their resilience to floods and storms.

We estimate upgrading costs with a systematic cross-country, bottom-up approach. This approach is based on country exposure to natural hazards and the additional costs that would be incurred to make exposed assets more resilient. We proxy the location of all infrastructure with the location of roads and railways. To identify which assets need strengthening, we use two detailed global maps: one shows the location of natural hazards and the other the location of roads and railways (Koks and others 2019). The share of exposed assets by country is approximated by the share of the kilometers of roads and railways that are exposed to natural hazards. A kilometer of road or railway is assessed to be exposed if its construction standards are such that it gets damaged at least once every hundred years. Construction standards are assumed to differ between high-income countries, upper-middle-income countries, and all others, and to increase with income following (Rozenberg and Fay 2019).

The incremental costs of making exposed assets more resilient are estimated using the average values corresponding to the set of technical options from (Miyamoto International 2019). Even as they are economically sensible, the technical solutions do not guarantee that assets cannot be damaged by natural hazards and do not include all possible options to reduce risks, including more cost-effective alternatives or more expensive options that could further reduce risks. Based on the exposure and incremental cost measures, we estimate the following:

- **Strengthening costs for investment projects** are computed using average investment projections over 2021 to 2025. Investment projections are multiplied by the estimated share of exposed assets, and by a unit cost of 15 percent. Hence, the average exposure of future projects is assumed to be the same as the exposure of existing assets. Public and private investment projections are from the World Economic Outlook (IMF 2020f). When projections are unavailable, we assume that future investment to GDP ratios remain constant at the last observed level in the IMF Investment and Capital Stock Dataset 2019. Achieving the Sustainable Goals would require additional investments (IMF 2019a). Those would need to be made more resilient and add to the costs. The costs are expressed in annual values.

- **Strengthening costs of existing assets** are computed as the capital stock that won’t be depreciated by 2030 (in 10 years), multiplied by the estimated share of exposed assets and by a unit cost of 50 percent. The total costs are annualized by assuming constant investment in percent of GDP over the next 10 years. We use the 2017 levels of public capital stock and the

---

2 These unit cost estimates are based on engineers and experts’ assessment of average strengthening costs (Hallegatte, Rentschler, and Rozenberg 2019; Miyamoto International 2019).
depreciation rates from the IMF Investment and Capital Stock Dataset 2019. In some cases, it may be more cost-effective to abandon some exposed assets or tear down and rebuild them better. The fraction of the capital stock that won’t be depreciated within 10 years is equal to $(1 – \delta)^{10}$, where $\delta$ denotes the depreciation rate.

The simple cross-country average of adaptation costs is estimated at 0.1 and 0.3 percent of GDP for strengthening investment projects and existing assets, respectively. These estimates are similar to the weighted averages presented in the main text because the few small countries with very high costs are averaged with many countries with very small cost estimates. Also, these estimates can seem low compared with the large stock of existing assets and investment projects but reflect the fact that only 10 percent of assets are estimated to be exposed to floods and storm on average.

The cost estimates of strengthening public assets vary considerably across nations. Costs tend to be lower for advanced economies because of higher construction standards and therefore smaller shares of exposed assets, and because of lower public investment as a share of GDP. However, advanced economies have a larger stock of existing assets, making the costs of strengthening these relatively closer to costs in other countries. Assets and investment projects in low-income countries and small developing states tend to be most exposed, thereby leading to high-cost estimates. The costs are highest for emerging economies because they typically combine larger exposure as in low-income countries and small developing states with large stocks of existing assets and investment projects.

Strengthening exposed future and existing private assets could cost, respectively, 0.4 and 0.6 percent of GDP annually between 2021 and 2025 (Annex Figure 2.1). These costs are estimated to be almost twice as large as in the public sector (main text Figure 3). In contrast with public sector cost estimates, private sector costs are more evenly distributed across income groups and across new and existing infrastructure. This reflects the fact that higher private investment and larger shares of private-owned infrastructure in more advanced countries compensate for lower exposure. As for Figure 3, these estimates do not correspond to optimal investment but represent strengthening costs that are expected to be lower than avoided damages in a large range of scenarios.

**Annex Figure 2.1. Adaptation Costs to Selected Current Climate Risks in the Private Sector (2021–25)**

Annual Costs of Strengthening Private Assets Resilience to Current Storms and Flood Risks

Sources: Hallegatte, Rentschler, and Rozenberg (2019); Hallegatte and others (2019); IMF, Capital Stock 2019 Dataset; IMF, World Economic Outlook database; and staff calculations.
Annex 3. The IMF’s Debt, Investment, Growth, and Natural Disaster (DIGNAD) Model: An Application to Developing Economies in Asia and the Pacific

The IMF’s workhorse DIGNAD model extends the Debt, Investment, and Growth (DIG) model of Buffie and others (2012) to analyze natural disasters and adaptation infrastructure. The DIGNAD model, developed in Marto, Papageorgiou, and Klyuev (2018), is a dynamic low-income or emerging-country open-economy model that incorporates natural disasters and resilient infrastructure to examine the nexus between public investment and growth, different financing strategies (external concessional, external commercial, and domestic), and fiscal reaction rules. It captures high rates of return on public capital, either standard or resilient, as well as significant inefficiencies in public investment and absorptive capacity constraints, which are pervasive in developing economies. The model captures the main mechanisms and policy issues of interest for debt sustainability analysis, particularly those associated with the linkages between public adaptation investment, economic growth, and debt.

In the model, a natural disaster has multiple adverse effects on the economy which can be mitigated by investing in resilient infrastructure. Natural disasters impact the economy through the following channels: (1) permanent damages to public infrastructure, (2) permanent damages to private capital, (3) temporary losses of productivity, (4) increased inefficiencies in public investment during the reconstruction process, and (5) an increase in risk premium for borrowing costs. Investment in adaptation infrastructure is costlier than investment in standard infrastructure but reduces the damages inflicted by a natural disaster (for example, seawalls) and depreciates at a lower rate. Investing in adaptation infrastructure is useful as a complement to conventional infrastructure as it raises the marginal product of other capital by helping withstand the impact of natural disasters, and crowds in private investment.

The growth-debt trade-off of boosting adaptation investment can be examined with calibrated model simulations. For example, IMF (2021c) calibrates a DIGNAD model as an economy whose macroeconomic indicators are averages for developing economies in Asia and the Pacific. The model is used to simulate two investment scale-up plans (standard investment versus investment in adaptation), and examine the evolution of growth and public debt after a large natural disaster hits the economy. Investment is financed by commercial debt and takes place over five years before the disaster strikes (in year 6), as reaping benefits from disaster resilience would require substantial accumulation of adaptation investment.

---

1 The development of the DIGNAD model is part of a research project on macroeconomic policy in low-income countries (IATI Identifier: GB-1-202960) supported by the U.K.’s Foreign, Commonwealth and Development Office (FCDO) and the partners in the IMF’s COVID-19 Crisis Capacity Development Initiative (CCCDI)—Belgium, Canada, China, Germany, Japan, Korea, Spain, Singapore, and Switzerland.
Annex Figure 3.1. The Positive Effects of Investing in Resilient Infrastructure on Growth and Debt Stability

<table>
<thead>
<tr>
<th>1. GDP Growth</th>
<th>2. Change in Public-Debt-to-GDP Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Percentage deviation from steady state)</td>
<td>(Percentage point deviation)</td>
</tr>
</tbody>
</table>

Source: IMF (2021d).

Adaptation investment, albeit costly, can make the economy resilient against natural disasters, limiting a post-disaster rise in public debt. The growth and public debt paths for the two investment scenarios are shown in Annex Figure 3.1. Standard investment is less costly than investment in adaptation but does not shield the economy from natural disasters. Post-disaster spending needs push debt on an unsustainable trend and imply significant output losses over the medium term. Post-disaster output losses are softened in the adaptation investment scenario, by more than half compared to the scenario of standard investment. More expensive adaptation investment implies higher public debt in initial years. Unlike debt in the standard investment scenario, however, the debt level stabilizes over the long term due to smaller and less persistent output losses and smaller reconstruction needs.

Better public investment management can lessen the growth-debt trade-off for adaptation investment. Weak management can lead to poor maintenance and wasteful investment in low-exposure areas or in assets that should be relocated because of overwhelming risks. The benefits of improved public investment management (PIM) efficiency are illustrated in Annex Figure 3.2, panel 1. If PIM efficiency improves from the lowest levels observed in the region (“low investment efficiency” scenario in Annex Figure 3.2, panel 1) to those of best performers (“high investment efficiency” scenario), output resilience against natural disasters further improves and public debt paths are brought down. The results echo those for the Solomon Islands (IMF 2018), which show that PIM reforms amplify the benefits of adaptation investment.

Financing adaptation investment with concessional external financing or revenue mobilization can also alleviate the growth-debt trade-off. Alternative financing options for adaptation investment are examined in Annex Figure 3.2, panel 2. Financing adaptation investment with foreign concessional loans can put public debt on a decreasing path after the disaster by freeing up resources to repay debt faster. Foreign concessional financing also reduces domestic financing needs by the government and avoids
crowding out private investment. Alternatively, countries can mobilize domestic revenues to finance adaptation investment. A consumption tax increase can put public debt on a faster declining path than under the concessional financing scenario, even though the tax burden negatively affects output by depressing private demand. While not included in the simulations in Annex Figure 3.2, panel 2, rationalizing government spending can also put public debt on a declining path.

**Annex Figure 3.2. The Role of Public Investment Management and Financing Reforms in Strengthening Adaptation Investment Strategies**

1. Public Investment Management Reforms

<table>
<thead>
<tr>
<th>GDP Growth (Percentage deviation from steady state)</th>
<th>Change in Public-Debt-to-GDP Ratio (Percentage point deviation)</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Graph" /></td>
<td><img src="image2.png" alt="Graph" /></td>
</tr>
</tbody>
</table>

2. Financing Reforms

<table>
<thead>
<tr>
<th>GDP Growth (Percentage deviation from steady state)</th>
<th>Change in Public Debt to GDP Ratio (Percentage point deviation)</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image3.png" alt="Graph" /></td>
<td><img src="image4.png" alt="Graph" /></td>
</tr>
</tbody>
</table>

Source: IMF (2021d).
References


Bellon, Matthieu, and Emanuele Massetti. 2022b. “Planning and Mainstreaming Climate Change Adaptation in Fiscal Policy.” IMF Staff Climate Note 2022/003, International Monetary Fund, Washington, DC.


Global Center on Adaptation. 2018. "Adapt Now: A Global Call for Leadership on Climate Resilience." Global Center on Adaptation and World Resources Institute, Rotterdam, Netherlands.


International Monetary Fund (IMF). 2016. “Small States’ Resilience to Natural Disasters and Climate Change—Role for the IMF.” IMF Staff Report, Washington, DC.


