

# The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies

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## Introduction

Since the 1990s, a series of natural disasters have caused economic losses in the tens of billions of U.S. dollars. Examples include the Northridge (United States) earthquake in 1994, the Kobe (Japan) earthquake in 1995, the 2004 Indian Ocean earthquake that caused the Asian tsunami, Hurricane Katrina (United States) in 2005, the 2011 earthquake and tsunami in Japan, and Hurricane Harvey (United States) in 2017. Moreover, the (inflation corrected) economic losses of natural disasters have been increasing over the last few decades, with the number of natural disasters causing substantial losses increasing by a factor of three since the 1980s (Hoeppe 2016). Population and economic growth are still the main drivers of rising losses from natural disasters, but anthropogenic climate change may increase the frequency and/or intensity of future extreme weather events (Intergovernmental Panel on Climate Change 2014). These trends highlight the importance of designing policies that can mitigate the impacts of such disasters on the economy and society.

A large and growing literature has estimated the direct and indirect economic impacts of natural disasters using a wide range of modeling and empirical approaches. However, to date, there has been no systematic review of this literature. This article seeks to fill this gap by reviewing this emerging literature, synthesizing its main theoretical, computational, and empirical methods and findings, and discussing insights into factors and actions that have been found to mitigate disaster impacts. We take stock of this literature to both identify gaps

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in our knowledge and provide guidance to policymakers as they seek to manage the risks and impacts of natural disasters.

Our review of the literature focuses on the direct economic impacts and indirect (macro)economic effects of natural disasters. Direct impacts refer to the damage to assets (e.g., property) caused directly by a natural disaster, with the losses occurring at the time of the disaster or shortly thereafter. Examples of direct economic losses include the destruction of residences, businesses, productive capital, infrastructure, crops, livestock, and (monetized) physical and mental health impacts. These direct losses are generally estimated using catastrophe models and measured using empirical data on losses. The direct impacts can lead to indirect impacts, which refer to changes in economic activity that follow the disaster. These include interruptions of economic activities as well as any positive spillover effects due to the substitution of production and the demand for reconstruction. Thus the indirect impacts capture the short- and long-term economic losses in economic production and consumption and any related economic recovery paths (Kousky 2014). These indirect effects of disasters—sometimes called higher-order effects—are predicted using macroeconomic theory and can be quantified using computational macroeconomic models. These predictions can be tested using empirical data and methods that focus on a variety of economic indicators, such as gross domestic product (GDP) level and growth, trade, and employment.

We limit our scope to the emerging literature on the immediate short run and the direct and indirect long-run economic impacts of natural disasters. We exclude two sizeable and important literatures. First, we do not discuss studies that use hedonic pricing methods to link housing prices to natural disaster risks and mitigating factors (see Barbier [2012] and Gopalakrishnan, Landry, and Smith [2018] for overviews). Second, we exclude studies that examine the impacts of disasters on either human health, well-being, and development (Kousky 2016) or life satisfaction (Hudson et al. 2019).

The remainder of the article is organized as follows. In the next section we present the theory that has been used to predict how natural disasters affect the macroeconomy. Then we review computational models that have been used to simulate and quantify the predicted impacts from natural disasters, including catastrophe, input–output, computable general equilibrium, and integrated assessment models. Next we assess the methodologies and key findings of the empirical literature, including factors that mitigate disaster impacts. We conclude by identifying lessons for policymaking and discuss an agenda for future research in this area.

## Theoretical Models of Natural Disaster Impacts on the Macroeconomy

There is little need to theorize about direct disaster impacts. Shaking, inundation, and high winds simply cause damage; we discuss the measurement and prediction of such direct impacts in the next section. In this section we focus on the theoretical models that have been used to explain the *indirect* economic impacts of natural disasters.<sup>1</sup> All such models simplify a complex economic reality into a mathematical representation of the most pertinent

<sup>1</sup>See appendix A in the online [supplementary materials](#) for a detailed review of these macroeconomic models as well as the relevant regional economic models, including model assumptions and key literature.

causal chains that trace the impacts of an exogenous natural disaster on the economic system. Typically the disaster is conceptualized as the sudden loss of production factors (such as labor and capital), to which the economic system adjusts, either returning to the predisaster equilibrium or shifting to a new one.<sup>2</sup>

### Models Based on Social Accounting Matrices

Most research on the indirect impacts of natural disasters builds on the predictions of input–output (I-O) and computable general equilibrium (CGE) models. Both build on a social accounting matrix that identifies all monetary flows between all sectors in an economy. I-O models assume a time-invariant, fixed-proportions production function for all economic sectors and predict how damages in one sector affect trade and related production output in all of the others. In contrast, CGE models assume stable behavior, reflected in stable demand and supply functions, and predict how natural disaster impacts change the demand, supply, and prices in various markets in equilibrium.<sup>3</sup> Both types of models clearly predict that natural disasters have negative impacts on the overall economy.<sup>4</sup> Although these models have the desired level of detail and can make quantified predictions, technology and behavior are usually assumed to be “fixed.” Thus these models only give a useful first impression of the order of magnitude and diffusion of effects; they are ill-equipped to predict dynamic adjustment processes, a characteristic that is especially unsatisfactory as time and space horizons expand.

### Models Based on Neoclassical Growth Theory

Given these drawbacks of I-O and CGE models, several authors have derived and tested more sophisticated hypotheses based on neoclassical growth theory,<sup>5</sup> which is also used in integrated assessment models (IAMs) of climate change and the economy. In its simplest form, this theory assumes an aggregate production function using capital and labor (with constant returns to scale), a fixed savings and depreciation rate, and diminishing returns to capital. Such models predict a gradual return to the predisaster steady state after any shock to the capital stock or labor supply. In these models, natural disasters can have a lasting economic impact only if they permanently shift the basic parameters that determine the steady state, especially savings (see [Berlemann, Steinhardt, and Tutt 2015](#)), depreciation, or productivity growth.

### Models with Endogenous Productivity

A key limitation of neoclassical growth models is that they assume, rather than explain, technical change; endogenous growth models seek to address this limitation. Vintage capital models are an early branch of endogenous growth models that assume capital always embodies the best available technology at the time the capital is constructed. Investment drives technology in these models, which predict that any accelerated depreciation of capital

<sup>2</sup>Appendix table 1 summarizes the key input and output variables and predictions of the most relevant types of macroeconomic models.

<sup>3</sup>We review applications of both types of models in more detail in the next section.

<sup>4</sup>See appendix table 1.

<sup>5</sup>See a detailed list of references in table A1 in the online [supplementary materials](#).

due to a disaster shock will result in higher productivity growth because technology will be updated. This is called the “build-back-better” hypothesis in the literature (e.g., [Klomp and Valckx 2014](#)).

In contrast, in AK models (where A represents productivity and K refers to the capital stock), output and output per worker are linked to the level of accumulated capital in use, implying that negative capital shocks have a lasting negative impact on output per worker. Finally, in models of learning, knowledge accumulates in people as they produce more, and the level of productivity is assumed to depend on variables like cumulative production or investment. In these models, the destruction of capital or labor may stimulate learning and productivity growth during reconstruction, but this productivity is not embodied in the new capital as is the case in vintage capital models.

These early branches of endogenous growth models already allow for some productivity change over time in response to natural disasters. Nevertheless, few natural disaster applications use the more recent endogenous growth models.<sup>6</sup> In these models, productivity growth is not an automatic side result of economic decision making; rather it is driven by economic agents who decide to allocate scarce and costly resources to knowledge creation (e.g., research and development) and commercialization (e.g., entrepreneurship).<sup>7</sup> The same applies to institutional growth models, which identify sound institutions as the fundamental causes of economic growth and development.<sup>8</sup>

## Regional Models

It is important to note that all of the types of macroeconomic growth models we reviewed<sup>9</sup> can be criticized for ignoring geography (e.g., [Krugman 2011](#)). Because it now builds so heavily on mainstream macroeconomic models, the emerging literature on the economics of natural disasters is also vulnerable to such criticism. Thus, as we will discuss later, one direction for future research should be to consider regional economic models, which explicitly take geography into account ([Capello 2015](#)). In fact, regional models of growth and development can be used to connect macrolevel indirect impacts (e.g., output losses) to microlevel direct damages (e.g., destroyed capital stock) by estimating them at the geographic level at which they occur; these local direct impacts can be assessed with catastrophe models, which we discuss in the next section.

## Computational Models for Simulating the Impacts of Disasters

The low probability that a natural disaster will occur in a particular area means that there are likely to be few historical observations for estimating losses. Moreover, the impacts of disasters are not always recorded in detail when disasters do occur. This is why computational models are used to simulate potential impacts from hypothetical (but realistic) or historical natural disasters. Direct impacts are estimated using so-called catastrophe models, which, for

<sup>6</sup>[Cuaresma \(2010\)](#) is a notable exception.

<sup>7</sup>See appendix A in the online [supplementary materials](#) for a list of these models.

<sup>8</sup>See appendix A in the online [supplementary materials](#).

<sup>9</sup>See the list in appendix table 1.

instance, offer detailed results on property losses. Direct disaster impacts can then be fed into macroeconomic models that simulate indirect economic effects. Such studies tend to use I-O and CGE models. Although these models do not provide precise predictions of economic effects after a disaster, they offer insights into economic processes that cause indirect impacts, from which lessons can be drawn about key vulnerable sectors and mitigating factors. This section reviews catastrophe and macroeconomic model approaches and their key results in more detail.

### Catastrophe Models: Estimating Direct Impacts from Natural Disasters

Catastrophe models use geographic information systems (GISs) to estimate the potential losses from specific natural disasters by simulating hypothetical physical characteristics of natural hazards, such as flood events, at a particular location. For instance, flood hazard maps indicate characteristics such as potentially flooded areas, inundation depths, and flow velocity for a flood with a specific probability of occurrence. The hazard characteristics are then used to calculate damage to exposed property, which is generally represented by land use or building values, based on assumptions about the land or building's vulnerability. Catastrophe models typically estimate the damage from natural hazards with various intensities and probabilities, from which annual expected damage is derived. The geographic scales range from local (e.g., city level) to regional to global ([de Moel et al. 2015](#)).

#### Applications of catastrophe models

Although catastrophe models generally focus on estimating property damage, they also estimate affected populations and potential casualties of specific natural disasters ([Jonkman et al. 2008](#)). Risk estimates from catastrophe models are used for a variety of purposes, including guiding the pricing of extreme weather insurance and informing public sector risk management strategies. For example, flood risk estimates from catastrophe models have been used in global-scale benefit–cost analyses of dike investments and climate change adaptation funds ([Ward et al. 2017](#)), countrywide benefit–cost analyses of optimal flood protection standards in The Netherlands ([Kind 2014](#)), and benefit–cost analyses that guide local building code policies in cities, including New York City ([Aerts et al. 2014](#)). Rather than providing estimates of ex post compensation for disaster losses, these studies provide information on the economic desirability of investing in reducing natural disaster risk ex ante. In their reviews of benefit–cost analyses of reducing natural disaster risk, [Shreve and Kelman \(2014\)](#) and [Mechler \(2016\)](#) find that although benefit–cost ratios differ significantly across contexts and risk reduction measures, they are typically well above unity, which means the measures are economically desirable. In fact, according to [Mechler \(2016\)](#), on average, the benefits of disaster risk reduction outweigh costs by a factor of four.

#### Assessing external validity

Given the limited number of observations of natural hazard characteristics and losses per location, it is difficult to assess the external validity of catastrophe models (i.e., whether

modeled outcomes match observations). [Molinari et al. \(2017\)](#) review approaches for validating catastrophe models, which include comparing modeled hazard characteristics and projected damages with observations from events. Modeled damages can differ significantly from observed damages, especially for large-scale analyses ([de Moel et al. 2015](#)), although local assessments may be more accurate. To illustrate this accuracy, a spatially detailed catastrophe model estimated that Hurricane Sandy caused \$4.2 billion of damages to housing in New York City, while actual housing damages were \$4.7 billion ([Aerts et al. 2014](#)).

### Refinements and limitations of catastrophe models

Partly due to increased computing capabilities and the availability of data with a high spatial resolution, catastrophe modeling approaches have become increasingly refined.<sup>10</sup> Nevertheless, sensitivity analyses indicate that catastrophe models continue to be characterized by important uncertainties, especially in the modeling of vulnerability ([Aerts et al. 2014](#)). In particular, the empirical basis for assumptions about the presence of protection infrastructure and the vulnerability of properties (i.e., the damage they will suffer under different hazard conditions) is very limited. Moreover, catastrophe models typically assume that vulnerability is constant over time and independent of the behavior of governments and property owners. In reality, however, vulnerability is a dynamic process. For example, improvements may be made to better protect properties against natural disaster damage in response to disaster events or changes in the intensity or frequency of natural hazards due to climate change. Public authorities and emergency services may similarly learn and adapt. With this in mind, recent research efforts have sought to improve the modeling of vulnerability by using agent-based models that combine catastrophe models with the (behavioral) economic decision making of agents involved in disaster preparedness and response (e.g., [McNamara and Keeler 2013](#)). This allows researchers to estimate how vulnerability changes in response to changing risks, the occurrence of disasters, or policy. In fact, using this approach, [Haer et al. \(2017\)](#) show that accounting for disaster preparedness behavior results in damage estimates that are lower by about a factor of two than standard catastrophe models that assume constant vulnerability.

### Macroeconomic Models: Quantifying Indirect Economic Impacts from Natural Disasters

Macroeconomic models are used to estimate indirect losses from natural disasters, and include I-O and CGE models. In this section we review estimates from these models as well as from IAMs, which estimate natural disaster losses under climate change scenarios and have been used for guiding climate policy.

#### I-O models

As noted earlier, I-O models, which are based on matrices that capture the trade flows of the production inputs and outputs of different sectors in an economy, examine how natural disasters affect these trade flows and the related short-run production outputs ([Okuyama and](#)

<sup>10</sup>In particular, GIS data on exposure of properties is now more widely available ([de Moel et al. 2015](#)).

Santos 2014).<sup>11</sup> Studies using I-O models have examined many types of natural disasters, focusing on the indirect economic consequences of the failure of critical infrastructure (e.g., ports) or disruptions in a variety of sectors (e.g., industry, construction, services). Several of the studies we reviewed use the inoperability I-O model (often called the IIM), which captures the inoperability of a sector that is directly impacted by a natural disaster. This inoperability distorts inputs supplied to other sectors, which causes indirect output losses and production costs and thus limits the final consumptions of goods. This means that I-O models capture economic *interdependencies* between sectors that are upstream and downstream of the supply chain of disrupted goods within a national or regional economy. This allows the researcher to examine how a loss in an area directly impacted by a disaster ripples through to other sectors and regions. The simplicity of I-O models allows for the inclusion of sectoral detail and a simple representation of local economic disaster effects. Moreover, the improved availability of data allows for a high spatial aggregation as well as an ability to downscale models to more detailed spatial scales. However, standard I-O models do not capture certain economic mechanisms that may influence the final outcomes of disaster impacts, such as supply side shocks on sectors that have specific production constraints, price changes that influence the demand for final and intermediate goods, technology changes that affect intermediate input requirements, input and import substitution, and adaptive behavior and other forms of economic resilience (e.g., working overtime to make up for lost production) during recovery periods.<sup>12</sup> Finally, I-O models have a constant linear structure (e.g., concerning how production relates to inputs), but disaster impacts may be the result of nonlinear economic processes. This means that I-O models may be oversimplified.

Several recent models, such as the adaptive regional input–output (ARIO) model, have sought to overcome these shortcomings of standard I-O models. Methodological innovations of the ARIO model include modeling price increases after a disaster (which limits demand), imposing sector-specific supply constraints or the use of overcapacity, adjusting the shape and duration of recovery periods, or including specific resiliency measures. Some of these studies find high indirect economic losses. For example, using the ARIO model, Hallegatte (2008) estimates that indirect losses account for 30 percent of the direct losses from Hurricane Katrina, that these losses increase nonlinearly with direct losses, and that they can even surpass them for extreme disasters. Another recent I-O model, the multiregional impact assessment (MRIA) model, shows that indirect losses depend on the geographic scale over which the impacts are estimated. For example, Koks and Thissen (2016) show that although an I-O model of an extreme flood event in Rotterdam harbor estimates high indirect losses (which exceed the direct losses), an MRIA model of the same event finds substantially smaller indirect losses because of substitution effects that increase output in regions that are not directly impacted. Similarly, using a global I-O model, MacKenzie, Santos, and Barker (2012) find that the 2011 earthquake and tsunami in Japan caused substantial economic losses (\$80 billion) in Japan, but it mostly had net macroeconomic benefits in other countries.

Moreover, the way in which resilience measures are modeled substantially influences I-O outcomes. This is illustrated by Rose and Wei (2013), who use a demand and supply

<sup>11</sup>Appendix B in the online [supplementary materials](#) presents details on the design of I-O models, the main results concerning disaster impacts, and mitigating factors.

<sup>12</sup>See appendix B in the online [supplementary materials](#) for details.

driven I-O model to estimate the losses from a disaster that causes disruptions to sea ports in Texas. They find that indirect losses depend significantly on the modeling of resilience measures, which mitigate the impacts of a port disruption at the impacted site or along the supply chain. More specifically, allowing for resilience measures (e.g., shipping rerouting, production rescheduling) is found to limit total U.S. economic losses by 95 percent, but such losses are \$166.8 billion when resilience is not included.

Overall, I-O studies show that although local economic losses from natural disasters can be important for certain sectors, the broader macroeconomic system has an inherent flexibility that moderates the aggregate impacts. In particular, negative impacts are at least partly offset by substitution, which results in increased production by companies that are not directly impacted and increased production for reconstruction. A consistent picture that emerges from sensitivity analyses that were conducted for the models we reviewed is that uncertainties are high and results largely depend on assumptions about resilience measures and recovery paths.<sup>13</sup>

### CGE models

CGE models provide a more flexible model framework than I-O models because they include demand and supply in various markets in equilibrium<sup>14</sup> and they are nonlinear (e.g., they account for economies of scale and nonlinear impact functions). CGE models usually simulate the impacts of natural disasters on economic activity by estimating how disruptions to the supply of goods and services affect GDP (through relative price and quantity changes) and considering input and import substitution possibilities for the demand of intermediate and final consumption goods. Because of this price flexibility, which typically represents long-run processes, it has been argued that CGE models are better able to represent the long-run economic consequences of natural disasters than I-O models (Rose and Liao 2005).

CGE models have been applied to a variety of natural disasters at the global, national, and local levels.<sup>15</sup> At the global or continental level, CGE models have examined large-scale problems such as sea level rise and related flood risk and have identified that coastal protection has a high potential to mitigate the economic costs (Bosello et al. 2012). Several CGE models of natural disasters have a more detailed spatial dimension (i.e., by estimating disaster impacts in a country or region). More specifically, several studies have used a catastrophe model to estimate direct disaster impacts, which are then integrated into a regional CGE framework. For example, Carrera et al. (2015) integrate the results of a spatially detailed catastrophe model that estimates the direct impacts of a flood of the Po River in Italy into a CGE model of three Italian regions. They find that the direct flood impacts occur in northern Italy, where there are also large indirect losses. These indirect losses are partly offset by small economic gains in areas not directly affected by the flood, which take over some of the disrupted production. In another example, Pauw et al. (2012) combine a hydrometeorological crop loss model with a regional CGE model to estimate the economic losses from

<sup>13</sup>See appendix B in the online [supplementary materials](#).

<sup>14</sup>This results from the simultaneous optimizing behavior of consumers and firms, subject to resource constraints and economic account balances.

<sup>15</sup>Appendix C in the online [supplementary materials](#) describes the model design and main results concerning disaster impacts and mitigating factors for a selection of such studies.

droughts and floods in Malawi. They find that the agricultural impacts of droughts and floods cause national economic losses that range from 1.1 percent to 18.8 percent of GDP per flood event. These impacts exacerbate income inequality and poverty at the household level.

CGE models have also been used to examine various resilience strategies that could significantly reduce losses from disaster events. For example, [Rose and Liao \(2005\)](#) show that the economic costs from the disruption of water supply during the Northridge earthquake could have been greatly reduced through water conservation and substitution, and that a mitigation strategy that replaces vulnerable pipes reduces total losses by almost half. Moreover, [Rose et al. \(2016\)](#) find that resilience measures that limit the impacts from port disruption (e.g., by recapturing lost production and sales at a later date) would significantly reduce the economic losses of a tsunami in California.

Overall, the flexibility of CGE models in terms of substitution possibilities and price changes that balance demand and supply makes them more suitable for studying the long-run economic consequences of disasters. Due to these characteristics, the sometimes high ratios of indirect to direct disaster losses in I-O models are not observed in these CGE applications, which highlights the important role of economic adjustment processes in limiting indirect disaster impacts.

### **IAMs of climate change impacts**

Several global (but often regionally differentiated) IAMs of climate change and the economy have been developed that estimate the impacts of climate change in GDP terms, estimate the social cost of carbon, and derive economically optimal pathways for reducing greenhouse gas emissions. The most well-known models are the Dynamic Integrated Climate–Economy (DICE)/Regional Integrated Climate–Economy (RICE), Framework for Uncertainty, Negotiation, and Distribution (FUND) and Policy Analysis of the Greenhouse Effect (PAGE) ([van den Bergh and Botzen 2015](#)). These models are based on a simplified version of neoclassical economic growth theory, because, with the exception of [Dietz and Stern \(2015\)](#), they assume exogenous economic growth in relation to climate change.

Although most IAMs estimate the aggregate economic impacts of climate change, some applications have focused on natural disasters. For example, using the FUND model, [Narita, Tol, and Anthoff \(2010\)](#) estimate that the global economic costs of extratropical storms (i.e., large-scale storms, excluding tropical cyclones) due to climate change will increase by 38 percent in 2100. [Diaz and Keller \(2016\)](#) adapt the DICE model to estimate the economic impacts of a disintegration of the West Antarctic Ice Sheet due to climate change (which causes an additional sea level rise of 3.3 meters). They find that the current optimal climate policy is largely insensitive to this disintegration because, due to discounting, the costs in the far future (2200) have almost no influence on present value costs. Others have argued that for intergenerational equity, lower discount rates should be assumed, which implies greater weights on future climate change impacts ([Stern 2013](#)). Using the PAGE model, [Dietz \(2011\)](#) shows that the use of a lower discount rate is an important assumption when including more extreme climate change risks, because a low discount rate substantially increases the present value of the economic costs of these risks.

A number of studies have reviewed the use of IAMs as tools for providing guidance about climate policy, including [Stern \(2013\)](#), [van den Bergh and Botzen \(2015\)](#), and [Tol \(2018\)](#).

These reviews highlight the great uncertainty of economic impacts, which is due partly to the incomplete or ad hoc inclusion of specific climate change risks in simplified damage functions. Moreover, it has been argued that the treatment of natural disasters in IAMs is incomplete and that current impact functions insufficiently capture the economic costs of sea level rise and extreme weather (Ackerman and Munitz 2012) and hence need to be updated.

## Empirical Studies of the Direct and Indirect Economic Impacts of Natural Disasters

With this background on theoretical and computational models, we next turn to a review of empirical studies of the economic impacts of natural disasters. First we discuss data sources and econometric methods. This is followed by a discussion of the main results concerning disaster impacts and mitigating factors.

### Data Sources

The most commonly used source of data on natural disasters is the Emergency Events Database (EM-DAT), compiled by the Centre for Research on the Epidemiology of Disasters (CRED). Similar databases such as NatCatSERVICE and Sigma, created by the reinsurance companies Munich Re and Swiss Re, have also been used, although less frequently, because they are not broadly publicly available. Limitations of EM-DAT include that it has variable thresholds for inclusion of events in the database and that damages are recorded as (uncorrected) monetary estimates from local authorities, which may be inflated shortly after a disaster. Disaster intensity measures from EM-DAT are likely to be correlated with GDP per capita, which is the main dependent variable in the literature, because losses are generally higher and better recorded in developed countries.

Given these data issues, many recent studies use definitions of natural disasters based on geophysical or meteorological variables, such as hurricanes (e.g., Hsiang 2010), or indices constructed from variables such as storms, floods, earthquakes, and extreme temperature (Felbermayr and Gröschl 2014). Such physical indicators of natural disasters are not subject to the endogeneity bias of the EM-DAT data and thus should be the data used in future research.

The wide range of possible direct and indirect impacts of natural disasters is reflected in the wide range of economic outcome data used in the literature. These outcome data include GDP, GDP growth rate, trade flows, death counts, employment, per capita income, expenditures, migration, housing and other asset values, and government transfers.<sup>16</sup>

### Econometric Methods

Most estimates of the economic impacts of natural disasters are based on regressions of aggregate variables (measured at the country level) on some measure of disasters, such as the number of disasters, the monetary damages, the number of fatalities, or hurricane

<sup>16</sup>Online appendix D presents all of these data sources and the variables constructed from them, as well as a summary of the empirical studies we reviewed.

intensity. The early literature (e.g., [Skidmore and Toya 2002](#)) tended to use cross-sectional regressions that related economic outcomes to disaster indicators, while controlling for potential determinants of growth.<sup>17</sup> Thus these regressions relied on across-country differences in natural disaster occurrence as the primary source of econometric identification. A central problem with such regressions is that even with the inclusion of detailed cross-sectional control variables, they may provide biased estimates of the effect of natural disasters. This is because there is a potential for omitted variable bias if determinants of the economic outcomes under study are not included in the model and are correlated with the disaster measures.

As a result of this potential bias, we found that almost all of the studies we reviewed use panel (i.e., longitudinal) data aggregated to the country-year, province-year, or county-year level. A key advantage of panel data is that they allow for the inclusion of location (e.g., country) fixed effects, which control for all time-invariant location-specific unobserved determinants of the outcomes and thus can help control for the effect of difficult to quantify attributes of a location, such as geographic features, culture and norms, and institutions. Because panel data regressions rely on within-location variation in disaster occurrence over time as the primary source of identification, these models allow the relationship between disasters and economic outcomes to be dynamic, and thus some studies allow for lagged effects of natural disasters.

## Main Findings of the Empirical Literature

Before discussing the findings of individual studies, it is useful to examine the findings of two recent meta-analyses of the empirical literature on the impacts of natural disasters. [Lazzaroni and Bergeijk \(2014\)](#) analyze 64 macroeconomic studies of the direct and indirect cost of natural disasters and find a significant negative effect of disasters in direct cost studies but an insignificant effect for indirect costs. Indirect disaster impacts are more likely to be negatively significant if an objective disaster indicator such as physical disaster intensity is used. [Klomp and Valckx \(2014\)](#) conduct a more focused meta-analysis on the indirect economic effects of natural disasters in terms of economic growth per capita. Based on 25 primary studies, they conclude that natural disasters have a significant negative effect on growth, an effect that increases over time and is strongest for climatic disasters in developing countries. Moreover, there are significant short-run declines in economic growth for climatic and geological disasters for which long-run effects are insignificant. Hydrometeorological disasters are found to reduce growth in both the short and long run. Overall, these findings suggest that both the direct and short-run indirect economic effects of natural disasters are generally negative, while negative long-run effects are observed for only certain hazards, such as hydro-meteorological disasters.

### Estimates of direct losses from natural disasters

The empirical literature on natural disasters is dominated by studies of indirect impacts. However, in one of the highly cited studies on direct impacts, [Kahn \(2005\)](#) examines the

<sup>17</sup>These include population and land area, baseline income levels, average education, political regimes, indicators of financial system development, institutions, openness to trade, and foreign direct investments.

determinants of the direct impacts of natural disasters, measured by fatalities. More specifically, he studies the role of income, institutions, and political and geographic factors in determining disaster impacts<sup>18</sup> and finds that higher income nations experience fewer deaths from natural disasters and that democracy and better institutions also reduce the death toll. Others have followed up and expanded on these findings, including [Kellenberg and Mobarak \(2008\)](#), who show that the fatality–income relationship is nonlinear, increasing at lower levels of per capita income and then decreasing.

A few other empirical studies estimate direct damages. For example, [Anttila-Hughes and Hsiang \(2013\)](#), which is described in greater detail later, find that typhoons in the Philippines cause destruction of household assets and aggregate physical damages. Evidence from other studies also suggests that the direct economic losses of natural disasters increase over time. The overall conclusion of these studies is that economic and population growth have been the key drivers of increases in direct natural disaster losses over time, although some recent studies find that part of this trend may be due to climate change ([Intergovernmental Panel on Climate Change 2014](#); [Estrada, Botzen, and Tol 2015](#)).

### Indirect losses from natural disasters

Here we review some of the most prominent papers in the large literature on indirect losses caused by natural disasters, based on their methodological contributions. [Felbermayr and Gröschl \(2014\)](#) have constructed a new database—GeoMet—that is based on physical (non-economic) measures of disaster intensity, such as earthquakes, volcanic eruptions, storms, floods, and extreme temperature events. Based on a panel regression that includes country and year fixed effects, they find that natural disasters have a robustly negative effect on the GDP growth rate and that the relationship is highly nonlinear for disaster intensity. To illustrate, they find that a disaster in the top 1 percent of the disaster index distribution reduces the GDP growth rate by 7 percent, while a disaster in the top 5 percent of the distribution reduces it by only 0.5 percent. They also compare their estimates, which are based on the GeoMet data, with estimates based on EM-DAT and NatCatSERVICE data. When the latter two databases are used to define natural disaster intensity, there is a statistically insignificant and unstable relationship between disasters and growth. [Felbermayr and Gröschl \(2014\)](#) argue that this difference in findings is due to endogeneity bias, because the disaster intensity measures in EM-DAT and NatCatSERVICE are economic measures (such as total monetary damages) rather than physical measures.

Several studies have used panel data methods to examine the impact of single or multiple hurricanes (also called storms, typhoons, cyclones, depending on the location of their occurrence). In an early example, [Hsiang \(2010\)](#) used a panel model with country fixed effects and data for 1970–2006 to study the effect of cyclone intensity (defined as energy dissipation) on economic activity (measured by GDP) in 28 Caribbean-basin countries. He finds a small effect of cyclones on total economic output, but when this effect is decomposed by industrial sector, both large negative and large positive output responses emerge. Specifically, then agriculture, wholesale, retail sales, and tourism sectors are all impacted negatively by cyclones, while the construction sector benefits from them, presumably because of reconstruction

<sup>18</sup>To this end, Kahn estimates OLS regressions relating fatalities from natural disasters to income using a panel of 73 countries for the 1980–2002 period.

efforts. [Hsiang \(2010\)](#) also finds evidence of a dynamic relationship between lagged cyclone intensity and current sectoral GDP, suggesting that the economic impact of cyclones may last beyond their year of occurrence.

[Anttila-Hughes and Hsiang \(2013\)](#) examine tropical cyclones using household-level data for the Philippines (one of the world's most typhoon-exposed countries). They find that the average typhoon affects both richer and poorer households, reducing annual household income (net of all transfers) by 6.6 percent in the short run. These losses persist for a few years after a typhoon, especially for poorer households. [Anttila-Hughes and Hsiang \(2013\)](#) also find that the income losses caused by a typhoon lead to a nearly one-for-one reduction in household expenditures in the Philippines, most notably expenditures related to human capital investments.

While most of the literature focuses on economic impacts of natural disasters in low- and middle-income countries, there have been some studies of impacts in more developed country settings. For example, [Strobl \(2011\)](#) examines the effect of hurricanes making landfall in the United States, using county-level data for 1970–2005. He constructs a hurricane destruction index based on a monetary loss equation, local wind speed estimates derived from a physical wind field model, and local exposure characteristics. He applies this measure to county fixed effect panel data and finds that a hurricane landfall in a county reduces the growth rate of per capita income by 0.45 percentage points, which is large compared to the average growth rate of 1.68 percent. An important component of the reduction in per capita income comes from an endogenous mobility response to the hurricane, whereby richer individuals are more likely to migrate out of the affected county.

[Leiter, Oberhofer, and Raschky \(2009\)](#) present one of the few studies of the effect of disasters on firm-level outcomes. Specifically they examine the effect of exposure to a major flood on employment, asset accumulation, and productivity. Using a panel of European firms, they find that floods lead to significant increases in assets and employment growth, while productivity is not significantly impacted. This finding suggests that after a flood, damaged production capabilities are offset by increased investments in assets and increased labor.

Overall, these empirical studies suggest that the indirect effects of natural disasters significantly reduce economic growth, especially in low-income countries.

### **Long-term effects of natural disasters**

Fewer studies measure the (indirect) economic effects of natural disasters over the longer term (i.e., multiple decades). This gap in the literature reflects important data challenges, including the fact that outcomes for the units affected by a natural disaster (household, cities, or countries) must be available for long periods of time after the disaster and that there must also be suitable control groups. We next discuss the few such studies that do exist.

In an influential study, [Skidmore and Toya \(2002\)](#) use EM-DAT data and a cross-sectional model to investigate the long-run relationship between natural disasters, capital accumulation, total factor productivity (TFP), and economic growth. Their baseline model relates average annual GDP growth over the 1960–1989 period to the total number of natural disaster events occurring in a country over the same period. They find that natural disasters predict increases in GDP growth rates and in TFP, which they argue is due to disasters

stimulating new technology adoption and updating of capital stock. However, an important limitation of this study is the potential for omitted variable bias due to the purely cross-sectional nature of the empirical analysis.

In a comprehensive study of the effect of cyclones on economic growth over the short and long term, [Hsiang and Jina \(2014\)](#) combine a country-year panel on GDP growth rates for almost every country over the 1950–2008 period with each country's exposure to cyclones.<sup>19</sup> Using an approach that allows for past cyclones to affect current GDP growth,<sup>20</sup> they find robust evidence of persistent and negative effects of disasters on GDP growth. For example, incomes do not fully recover, even 20 years after a cyclone strikes, and an additional meter per second of wind exposure lowers per capita income by 0.4 percent 20 years later. These effects are found for both rich and poor countries, with higher losses in countries where cyclones are not as frequent; this is consistent with the idea that long-term adaptation helps to mitigate the negative effects of cyclones.

An important implication of the long-term impact studies is that natural disasters, in particular cyclones, reduce economic growth for several years beyond the year of the disaster. This means that studies that quantify only the immediate impacts are likely to underestimate the total impacts of disasters.

## Identifying Mitigating Factors

Many studies have attempted to identify individual or aggregate factors and actions that mitigate the detrimental effects—direct or indirect—of natural disasters. Mitigation actions can be classified as predisaster (e.g., public information campaigns, individual insurance and defensive investments, public defensive investments) and postdisaster (e.g., public information, direct disaster relief aid). The literature suggests that country-level factors such as income, institutions, average education, urbanization, infrastructure, trade openness, and financial development and integration can also affect the severity of natural disaster impacts.<sup>21</sup> Some studies also quantify the differential impact of natural disasters based on different levels of historical exposure to natural disasters. For example, [Hsiang and Jina \(2014\)](#) find that cyclones have smaller economic impacts in countries that are frequently exposed to cyclones. Such differences in disaster-related damages across the exposure spectrum are consistent with different levels of investments in protective capital that are driven by natural disaster risks.

Another key finding is that although higher income countries suffer higher direct property losses from natural disasters ([Hoeppe 2016](#)), they experience lower fatalities and smaller economic growth impacts ([Kahn 2005](#)). Possible explanations for this finding include the fact that richer nations may have better buildings (and better building codes), better-developed health care systems and information systems, and more resilient economies, which are better able to cope with shocks ([Kahn 2005](#)).

The literature has considered other possible mitigating factors. For example, in a country-level panel regression, [Noy \(2009\)](#) finds that countries with higher literacy rates, better institutions, and a higher degree of trade openness suffer smaller natural disaster losses.

<sup>19</sup>This is measured as wind force on a  $1^\circ \times 1^\circ$  grid.

<sup>20</sup>More specifically, they use a country and year fixed effects approach with a distributed lag specification.

<sup>21</sup>See appendix D in the online [supplementary materials](#).

Toya and Skidmore (2007) also find that increases in average education and trade openness reduce damages as a share of GDP. Noy (2009) and Toya and Skidmore (2007) use EM-DAT data in their analysis, but Felbermayr and Gröschl (2014) find the same results using GeoMet data. Specifically, Felbermayr and Gröschl find that disasters have smaller impacts on GDP growth in more democratic countries and in countries that are more open to trade and have better-developed financial markets.

Overall, the results concerning mitigating factors and actions point towards the advantages of having a developed, diversified, and open economy with sound institutions. These empirical results are also consistent with the results from CGE and I-O models, which highlight the mitigating effects of substitution possibilities, including trade, in offsetting lost production from sectors that are directly impacted by a disaster.

## Conclusions: Lessons for Policymakers and Directions for Future Research

This article has reviewed the rapidly growing literature on the economic impacts of natural disasters and synthesized its main theoretical, computational, and empirical methods in order to distill the main findings and identify insights into factors that mitigate disaster impacts. Our review has shown that natural disasters have significant negative direct economic consequences, like high property losses in developed countries and casualties in developing countries. Net macroeconomic (i.e., indirect) losses are overall negative, but are likely to be small for large developed economies, as they are better able to cope with negative production shocks (e.g., compensating for lost production with increased production elsewhere). These indirect economic impacts are generally more severe for low-income countries and smaller, less-diversified economies.

### Lessons for Policymakers

Given the increase in natural disaster losses in recent decades and the expected increase in the frequency and severity of natural hazards as a result of climate change, it is imperative for policymakers to have reliable information about both local natural disaster risks and effective risk mitigation measures and policies. Evaluating the impacts of a natural disaster *ex post* is useful for identifying lessons for risk management policies. However, being able to better predict them *ex ante* is even more useful and important. From our review of methods, it is clear that substantial progress has been made in recent decades in the development of complementary approaches for assessing natural disaster risk *ex ante*. For example, catastrophe models offer insights into *direct* economic impacts of disasters such as floods (e.g., property damages, casualties) on a detailed spatial scale, which is useful for designing local natural disaster risk management policies such as evacuation policies, building code policies, and flood protection infrastructure. In contrast, by providing upper and lower bound estimates (respectively) of the *indirect* economic impacts of natural disasters, I-O and CGE models offer insights into sectors, specific companies, and critical infrastructure that are vulnerable to natural hazards. This information can then be used for prioritizing protection of key infrastructure or economic activities and

for directing reconstruction aid. However, because I-O and CGE estimates of disaster impacts rely on simplifying assumptions, they can provide only general insights into the indirect economic consequences of disasters, and thus they should not be viewed as prediction or forecasting tools.

Our review suggests a number of lessons for policymakers at the local, national, and international level. Benefit–cost analyses of natural disaster risk reduction measures suggest that these measures are economically desirable. Thus national governments could, for example, limit disaster impacts through regulations, installing prevention measures such as flood protection, and setting up early warning systems. Local governments, like cities, are well positioned to fine tune disaster risk management policies for local risks, through measures such as zoning and building code policies, evacuation planning, and emergency response. Companies and households can also take action to limit the impacts of disasters, for example, through disaster-resilient building practices. Moreover, the findings of the I-O and CGE literature suggest actions that could substantially limit business interruption losses following disasters, including having sufficient inventories of production inputs, and having a flexible large network of suppliers of production inputs.

Moreover, the macroeconomic models and empirical literature suggest that policymakers should strive to promote economic resilience by maintaining a vibrant, flexible, and diversified economy that is able to cope with shocks. There are, however, substantial differences between sectors, and impacts are very localized within a country; this means that policies need to address the large distributional effects of disasters. Financial compensation arrangements (like postdisaster relief and [public–private] insurance systems), societal safety nets, and countercyclical government spending could be used to facilitate recovery and mitigate the indirect economic and distributional impacts of disasters.

At the international level, the key natural disaster issue is climate change. An internationally coordinated approach is needed to mitigate greenhouse gasses. IAMs of climate change and the economy can be used to guide economically optimal pathways for greenhouse gas emission reduction, while also considering potential increases in natural disaster risk as a result of climate change. Thus these models can inform global climate policy targets, but given their uncertainty, the results should be interpreted with caution. Moreover, postdisaster aid increasingly requires coordination at the international level. This is because fatalities and indirect losses are highest in relatively small low-income countries, which generally do not have adequate institutions or resources for risk management and financial compensation.

## Directions for Future Research

Despite progress in theoretical and quantitative assessments of the economic impacts of natural disasters, further research is needed to improve the reliability of these assessments. For instance, an important finding of our review is that macroeconomic theoretical and computational models of natural disasters often lack spatial detail; these models, as well as many empirical studies, ignore geography or operate on a large geographical scale, like a region or country. Thus these approaches fail to consider that most natural disasters first have *localized* impacts; where and with what intensity the disaster hits matters. Moreover, negative local impacts can be mitigated or reinforced by positive or negative indirect economic effects

elsewhere. Another important observation from our review is that the modeling and empirical approaches for assessing the economic impacts of natural disasters have developed as two independent branches of the literature and appear to have made little use of each other's results.

With these limitations of the current theoretical, computational, and empirical approaches in mind, we conclude with several suggestions for future research.

- Future theoretical models should build upon recent advances in regional economics,<sup>22</sup> whose models consider geography and can thus be connected to natural hazards at the appropriate spatial level. Depending on where the disaster hits and its intensity, the economic effects can be local or spread far and wide, and they can be positive, negative, or both in the short and long run, which means predictions of impacts can become ambiguous. Nevertheless, regional models are able to provide a deeper understanding of the channels for disaster impacts and the causal links between these impacts and economic outcomes.
- Many catastrophe models do assess natural disaster risk at a detailed spatial scale, but information on the *local* vulnerability of properties and economic assets to natural hazards is scarce. A further complication is that this vulnerability depends on disaster preparedness, which may change in response to changing risks and disaster events. Thus research is needed to improve the vulnerability component of catastrophe models by using improved data on local disaster preparedness. Moreover, agent-based models that explicitly incorporate individual decisions concerning disaster risk could be integrated into catastrophe models to estimate vulnerability dynamically, based on natural disaster preparedness by heterogeneous agents and the interactions between them (Aerts et al. 2018).
- The recommendation to link to agent-based models also applies to CGE models, which generally assume that consumers and firms respond optimally to disaster impacts. This strong assumption is likely to be unrealistic, and can be weakened in agent-based models, which allow for suboptimal (i.e., boundedly rational) responses.
- It is also important for I-O and CGE models to build upon recent advances, which include geographical detail and the ability to estimate the inoperability of specific sectors after a disaster, using spatially detailed empirical data of impacts or by linking these models with geographically refined catastrophe models (e.g., Fan, Fisher-Vanden, and Klaiber 2018).
- Empirical approaches for estimating the economic impacts of disasters could also be improved by making use of advances in remote sensing and the dissemination of GIS data products, such as weather records that measure local physical characteristics of disasters, and local measurements of economic activity that use satellite imagery (see, e.g., Corral and Schling 2017). This would allow for a more reliable estimation of the local impacts of disasters.
- Few of the I-O and CGE models we reviewed for this article have been tested and verified with empirical data. This is also true for the impact functions of IAMs and how they

<sup>22</sup>See appendix A in the online [supplementary materials](#) for a detailed discussion of these regional economic models.

capture natural disaster risks. Thus there is a need to better connect the modeling literature with the expanding empirical literature. In particular, research is needed that focuses on testing the realism of the assumed resilience measures and economic adjustment processes to shocks in I-O and CGE models in order to improve the empirical basis for these assumptions.

- Along these lines, the theoretical and empirical literatures both need to further develop and test hypotheses about the *causal mechanisms* through which natural disasters affect the economy. Many, if not all, of the estimated effects of mitigating actions have been identified using cross-sectional variation, which can be unreliable due to problems such as omitted variable bias and potential endogeneity. Thus another priority for future research should be to design studies that rely on experimental or quasi-experimental variation in mitigating factors or actions (i.e., variation that arguably is exogenous to natural disaster risk) in order to identify causal mechanisms.
- Finally, more research is needed on long-term impacts (e.g., beyond 5 years) of natural disasters.

**Appendix Table 1.** Summary of main macroeconomic model families

Model family	Key input variables	Key output variables	Predicted outcomes			
			Closed economy		Open economy	
			Short run	Long run	Short run	Long run
Input–output models	Capital (–)	{GDP, GDP/L, sectoral outputs}	{–,–,–}	{–,–,–}	{–,–,–}	{–,–,–}
	Labor (–)		{–,–,–}	{–,–,–}	{–,–,–}	{–,–,–}
	Intermediates (–)		{–,–,–}	{–,–,–}	{–,–,–}	{–,–,–}
	Productivity (–)		{–,–,–}	{–,–,–}	{–,–,–}	{–,–,–}
Computable general equilibrium models	Capital (–)	{GDP, GDP/L, sectoral outputs}	{–,–,–}	{–,–,–}	{–,–,–}	{–,–,–}
	Labor (–)		{–,–,–}	{–,–,–}	{–,–,–}	{–,–,–}
	Intermediates (–)		{–,–,–}	{–,–,–}	{–,–,–}	{–,–,–}
	Productivity (–)		{–,–,–}	{–,–,–}	{–,–,–}	{–,–,–}
Vintage capital models	Capital (–)	{GDP, GDP/L, sectoral outputs}	{–,–,–}	{+,+,+}	{–,–,–}	{+,+,+}
	Labor (–)		{0,0,0}	{0,0,0}	{0,0,0}	{0,0,0}
	Intermediates (–)		{0,0,0}	{0,0,0}	{0,0,0}	{0,0,0}
	Productivity (+)		{0,0,0}	{+,+,+}	{0,0,0}	{+,+,+}
Neoclassical growth models	Capital (––)	{GDP, GDP/L}	{–,–,–}	{0,0}	{0,0}	{0,0}
	Labor (––)		{–,++}	{–,0}	{0,0}	{0,0}
	Depreciation (+)		{0,0}	{–,–}	{0,0}	{0,0}
	Savings (+)		{0,0}	{+,+}	{0,0}	{0,0}
	Productivity (+)		{0,0}	{+,+}	{0,0}	{0,0}
AK models	Capital (––)	{GDP, GDP/L}	{–,–,–}	{0,0}	{0,0}	{0,0}
	Labor (––)		{–,++}	{–,0}	{0,0}	{0,0}
	Depreciation (+)		{0,0}	{–,–}	{0,0}	{0,0}
	Savings (+)		{0,0}	{+,+}	{0,0}	{0,0}
	Productivity (+)		{+,+}	{+,+}	{0,0}	{0,0}
Learning models	Capital (––)	{GDP, GDP/L}	{–,–}	{+,+}	{0,0}	{0,0}
	Labor (––)		{–,++}	{–,0}	{0,0}	{0,0}
	Depreciation (+)		{0,0}	{–,–}	{0,0}	{0,0}
	Savings (+)		{0,0}	{+,+}	{0,0}	{0,0}
	Productivity (+)		{0,0}	{+,+}	{0,0}	{0,0}
Endogenous growth models	Capital (––)	{GDP, GDP/L}	{–,–,–}	{0,0}	{0,0}	{0,0}
	Labor (––)		{–,++}	{–,0}	{0,0}	{0,0}
	Depreciation (+)		{0,0}	{–,–}	{0,0}	{0,0}
	Savings (+)		{0,0}	{+,+}	{0,0}	{0,0}
	Productivity (+)		{+,+}	{+,+}	{0,0}	{0,0}
Institutional growth theory	Capital (––)	{GDP, GDP/L}	{–,–,–}	{0,0}	{0,0}	{0,0}
	Labor (––)		{–,++}	{–,0}	{0,0}	{0,0}
	Depreciation (+)		{0,0}	{–,–}	{0,0}	{0,0}
	Savings (+)		{0,0}	{+,+}	{0,0}	{0,0}
	Productivity (+)		{+,+}	{+,+}	{0,0}	{0,0}
	Institutions (–)		{–,–,–}	{0,0}	{0,0}	{0,0}

Notes: Table contains family name (column 1), their key input variables (which are the point of entry for the disaster impacts [column 2]), a vector of endogenous output variables (column 3), and short- and long-run predictions for a closed and open economy (columns 4–7). Labor is assumed immobile. Open refers to trade in goods and services and capital. –, 0, and + stand for negative, zero, and positive effects, respectively, on listed output variables. L = Labor.

Source: The authors. See online [supplementary materials](#) for detailed references, methodologies, and results.

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