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Climate Shocks in the Anthropocene Era

Should Net Domestic Product Reflect Climate Disasters?

Leonard Nakamura
Emeritus Economist, Federal Reserve Bank of Philadelphia
Economic Statistics Centre of Excellence

Brian Sliker
Bureau of Economic Analysis

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Leonard Nakamura*
Federal Reserve Bank of Philadelphia
Economic Statistics Centre of Excellence

Brian Sliker
Bureau of Economic Analysis

Abstract

The asset costs of natural disasters in the United States grew rapidly from 1980 to 2023, with the trend rising 4.9 percent annually in real terms to $90 billion in 2023. Much of this trend in costs is likely due to climate change, and as a loss of assets implies a faster depreciation of real assets. We argue that the expected depreciation from these events should be included in Consumption of Fixed Capital (CFC), leading to lower levels and slightly lower growth rates for Net Domestic Product (NDP) and Net Domestic Investment. We use Poisson pseudo-maximum-likelihood regressions to estimate this expectation and generate our experimental measure of costs. An alternative calculation of CFC and NDP might directly include the time series of costs incurred rather than the far smoother expectation; this was the procedure adopted before 2009 and resulted in abrupt changes in NDP.

Keywords: Climate Change, Anthropocene, Depreciation, National Accounts, Disasters
JEL codes: Q54, Q56, C82

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* Nakamura is an emeritus economist in the Research Department of the Federal Reserve Bank of Philadelphia. Email: leinakam@msn.com. Sliker was an economist at the Bureau of Economic Analysis, U.S. Department of Commerce. We thank Scott Wentland, Abdul Munasib, Allison Derrick, Marshall Reinsdorf, Rachel Soloveichik, Bryan Parthum, and Wesley Ingwersen as well as three anonymous referees for helpful comments on this paper. We particularly thank Adam B. Smith for his comments, and we thank him and NOAA for their generous provision of data. We thank participants at the ESCoE 2022 Conference on Economic Measurement, the US Interagency Working Group on Hazards and Natural Capital meeting, and the Federal Reserve Committee on Climate and Economic Activity seminar.

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I. Introduction

We now live in an era in which human activity has a large impact on nature, so much so that some geologists have proposed that we are in a new geological era, the Age of the Anthropocene. Unfortunately, as Dasgupta (2021) has noted, nature is silent in economic discourse. It is therefore left to us to speak for nature; this is the rationale for efforts to create the National Strategy to Develop Statistics for Environmental-Economic Decisions (Office of Science and Technology Policy, 2023) within the framework of the UN System of Environmental Economic Accounting.

Human impacts on the Earth's weather systems through greenhouse gases are rising. Intergovernmental Panel on Climate Change reports (IPCC, 2021, 2023) note, with high confidence, that climate change has resulted in a trend in the rise of global extreme weather and climate events and, in turn, their costs. The US National Climate Assessment states there is a conspicuous and continuing rise in the costs of weather and climate disasters in the United States (Hsiang et al., 2023). How much of this rise is due to climate change and how much is due to increases in economic activity in disaster-prone regions is an important question but not one we pursue here.

If capital losses from disasters are rising, where should they appear in National Income Accounts? Disaster asset losses can be placed either in Consumption of Fixed Capital (CFC) or in Other Changes in the Volume of Assets (OCVA). When they are placed in CFC, they impact Net Domestic Product (NDP), National Income, Net Domestic Investment (NDI), and related aggregates because CFC is subtracted from Gross Domestic Investment to produce NDI, reducing Gross Domestic Product (GDP) to NDP. OCVA was introduced in the 2008 version of *System of National Accounts* (2008 SNA), in large part to shield NDP from the large movements caused by catastrophic losses.

Our proposal in this paper splits asset disaster costs into two components: an underlying trend and the residual shocks around that trend. The current methodology used by the US National Income Accounts (NIA) places all asset disaster costs in OCVA, while the NIA methodology before 2009 was to include them in CFC.[1] Our proposal is to place the trend in CFC and the residual shocks in OCVA. The pre-2009 methodology resulted in large quarterly swings in NDP relative to GDP. The current methodology removes those swings and smooths NDP but at the cost of missing the rising trend of disaster costs. The three methodologies are illustrated in the schematic Table 1.

We propose to use the National Oceanic and Atmospheric Administration's (NOAA) time series of billion-dollar weather and climate disasters (BWCD) as one measure of disaster costs. This data set is a pioneering effort to account for climate disaster costs. These costs include some economic costs that are not asset losses, such as crop losses to drought, and so overestimate total depreciation costs; in addition, they exclude asset costs from disasters such as earthquakes, terrorist attacks, and the like. We also use less well-documented disaster cost data collected by the Bureau of Economic Analysis (BEA) as part of its measurement of Other Changes in the Volume of Assets. These include only the very largest asset disaster costs, so they are an underestimate of total asset disaster costs, and because such data are sporadic, there is no systematic methodology for their collection.

[1] Both CFC and OCVA are subtracted from fixed capital assets, so there is no impact on the total capital, just on Net Domestic Product, National Income, and related aggregates.

Shifting from depreciation analysis to personal consumption expenditures of insurance services, property and casualty insurers raise their insurance premiums when expected losses rise. Expected value added for the property casualty insurers should not be affected to the extent that the increase in premiums reflects these costs only. If past trends can be projected to future expectations, the trend of disaster losses may aid in measuring these insurance services more accurately.

NOAA has constructed a time series of BWCD in the United States from 1980 to the present. They estimate the cost of individual disaster events resulting in $1 billion in economic losses or more, where these are measured in real dollars of the most recent year (2023), deflated by the consumer price index (CPI). Under this methodology, the billion-dollar criterion evolves over time—as the CPI rises over time and the base year changes, more events are added in earlier years. Disasters are divided into seven types: flood, drought, freeze, wildfire, and three types of storms (winter, tropical cyclone, and severe). This time series is built upon governmental and private insurance data, with the insurance estimates adjusted for uninsured costs. These costs do not include deaths (the value of a human life) or human distress. They do include temporary losses such as crop losses, business interruptions, and loss of housing services, which we are able to remove only crudely below, in Section IV. In the decade from 2014 to 2023, the average annual NOAA cost was $109 billion, as deflated by the CPI-U in February 2023 dollars, or 0.45 percent of GDP, similarly deflated.

The analysis we perform suggests that disaster costs have a large variance and are growing at a real rate of roughly 4.9 percent annually, appearing to double every 14 years. Expected costs from these disasters have risen in nominal terms from 0.1 percent to 0.4 percent of NDP; if these costs are included in CFC, NDI is reduced by 7 percent in 2023. We can further argue that it might be useful to include the unexpected component of disaster costs, which we argue should be in OCVA, with the trend in an Expanded GDP satellite account measure of CFC.

II. Existing Literature

This paper explores how to include the economic costs of weather and climate disasters in the national accounts, complementing work that includes environmental effects on Natural Capital. It does so by extending to physical assets the work of Reinsdorf et al. (2017), who incorporate expected *financial* losses in the national accounts. There is also a literature on trends in disaster costs, including work on insurance costs (Bevere and Orwig, 2015) and on US weather and climate disasters (Smith and Katz, 2013; Shukla, 2021). Al Kazimi and Mackenzie (2016) have a useful survey of work studying the economic costs of natural disasters and other calamities. An important question about climate and weather events is whether their costs are fat-tailed, which we investigate in Section V. Coronese et al. (2019) discuss the sharp rise in global weather and climate catastrophes and use quantile regressions to show rapid increases in the tail of such shocks. Weitzman (2009, 2011, 2014) has emphasized the importance of very large tail events in climate risks and the discounted social costs of these risks.

III. National Accounts Methodology

The question we address here is to what extent CFC should include the *expected* or trend costs of weather and climate disasters and thus whether these expected costs should impact NDP and related aggregates.

Weather and climate disasters are included in the section "The Other Changes in the Volume of Assets Account" in chapter 12 of 2008 SNA. Basically, Other Changes in the Volume of Assets are changes to capital assets that do not flow *normally* from economic activity:

> 12.46 The volume changes recorded as catastrophic losses in the other changes in the volume of assets account are the result of large scale, discrete and recognizable events that may destroy a significantly large number of assets within any of the asset categories. Such events will generally be easy to identify. They include major earthquakes, volcanic eruptions, tidal waves, exceptionally severe hurricanes, drought and other natural disasters; acts of war, riots and other political events; and technological accidents such as major toxic spills or release of radioactive particles into the air. Included here are such major losses as deterioration in the quality of land caused by abnormal flooding or wind damage; destruction of cultivated assets by drought or outbreaks of disease; destruction of buildings, equipment or valuables in forest fires or earthquakes. (*System of National Accounts, 2008*, 2009, p. 208)

These disasters are not included in Consumption of Fixed Capital unless they are included in accidental normal damage. As in chapter six in 2008 SNA:

> 6.240 Consumption of fixed capital is the decline, during the course of the accounting period, in the current value of the stock of fixed assets owned and used by a producer as a result of physical deterioration, normal obsolescence or normal accidental damage. The term depreciation is often used in place of consumption of fixed capital but it is avoided in the SNA because in commercial accounting the term depreciation is often used in the context of writing off historic costs whereas in the SNA consumption of fixed capital is dependent on the current value of the asset. (*System of National Accounts, 2008*, 2009, p. 123)

Prior to 2009, the measure of Consumption of Fixed Capital in the US National Income and Product Accounts (NIPA) included catastrophic losses. When Hurricanes Katrina and Rita devastated the Southeastern states in August and September of 2005, quarterly annualized nominal CFC rose from $1.49 trillion (Q2 2005) to $1.90 trillion (Q3 2005) before falling back to $1.56 trillion (Q4 2005). As a consequence, nominal National Income fell at a 5.8 percent annual rate from Q2 to Q3, and then rose at an 18.9 percent rate from Q3 to Q4, while nominal GDP rose at a 7.3 percent rate and then a 5.2 percent rate over the same quarters.[2]

In 2009, the US NIPA was revised to align with the 2008 SNA, in which disasters were removed from CFC and placed into OCVA. As a consequence, nominal CFC is now recorded rising steadily during this period, in trillions ($1.95, $1.99, $2.03). This change in the measurement of CFC prevents wild swings in quarterly growth rates but at the cost of removing the trend increase in capital losses. We therefore propose to put the trend—the expected path of disasters—into CFC while excluding the unexpected part of these disasters.

We contend that, to the extent that weather and disaster-related costs are rising faster than NDP or CFC, the "normal rate of accidental damage" has changed and that removing all disaster costs from CFC means it no longer includes these trends. Instead, measures of CFC should change to accommodate the new normal component in accidental damage by including the trend in these disaster costs.

In National Income methodology, this paper relies upon Reinsdorf et al. (2017) which discusses how to include expected losses in finance to improve SNA methods. For example, credit card interest payments to financial intermediaries overstate the net expected interest from credit card debt, as expected losses due to borrower defaults are high. The consumer services of

[2] Survey of Current Business, BEA, August 1996, https://apps.bea.gov/scb/issues/1996/scb-1996-august.pdf.

financial institutions include Financial Intermediation Services Indirectly Measured (FISIM), which under SNA is measured as the difference between interest received by financial intermediaries and the interest paid to consumers. If the credit card interest rate includes a large risk premium for losses, then FISIM overstates value added, and if expected losses are subtracted from the credit card interest rate, a more appropriate FISIM may be calculated. This argument led to a change in the BEA's treatment of FISIM to incorporate certain expected losses by financial intermediaries (Hood, 2013).

We argue that normal declines in the value of assets due to the expected component of weather and climate disasters ought to be included in Consumption of Fixed Capital. Below in Section V, we calculate the trend in disaster losses over time to estimate the size of this trend component. If we view the expected losses of catastrophes as part of CFC, then this will mean lower levels and smaller growth rates of NDP and NDI.

A related consideration is how to account for non-life insurance activities as part of personal consumption expenditures for insurance. The measure of the insurers' value added is premiums net of expected losses. What do we mean by expected losses of catastrophes? What is the normal part of such losses, which are likely to appear in non-life insurers' calculations of insurance premia? If an insurer raises insurance premiums because of a rise in expected accidental loss from catastrophes, we contend that increase should not be part of the insurers' value added, as the insurers do not expect to, on net, earn more from the insurance contract. At present, catastrophes are included in costs but are spread out over the 20 years following the event. If there is a rising trend in catastrophes, then the cost series will systematically lag expected costs. See page 5.68 in the Technical Note to Chapter 5 of the BEA's National Income and Product Accounts Handbook for BEA's treatment of catastrophes for non-life insurance in US personal consumption expenditures.

Unfortunately, we cannot estimate the trend in these household non-life insurance losses with the data currently available. It is possible that a subset of the NOAA data could be developed to help fill this data gap.

IV. Data from NOAA and BEA on Disaster Costs

NOAA's National Centers for Environmental Information collects data on Billion-Dollar Weather and Climate Disasters:

> More than one dozen public and private sector data sources help capture the total, direct costs (both insured and uninsured) of the weather and climate events. These costs include: physical damage to residential, commercial, and municipal buildings; material assets (content) within buildings; time element losses such as business interruption or loss of living quarters; damage to vehicles and boats; public assets including roads, bridges, levees; electrical infrastructure and offshore energy platforms; agricultural assets including crops, livestock, and commercial timber; and wildfire suppression costs, among others. However, these disaster costs do not take into account losses to: natural capital or environmental degradation; mental or physical healthcare related costs, the value of a statistical life (VSL); or supply chain, contingent business interruption costs. Therefore, our estimates should be considered conservative with respect to what is truly lost, but cannot be completely measured due to a lack of consistently available data. Sources include the National Weather Service, the Federal Emergency Management Agency, U.S. Department of Agriculture, National Interagency Fire Center, U.S. Army Corps, individual state emergency management agencies, state and regional climate centers and insurance industry estimates, among others. (NOAA National Centers for Environmental Information, 2024)

Briefly, much of the data is drawn from FEMA disaster estimates and from private insurance sources. Estimates of uninsured losses are also included. The time element losses, such as business interruption or loss of living quarters, should not be included as capital costs; these are deducted from other parts of NDP (e.g., residential services and industry output).

The published data series is not limited to the 50 US states and the District of Columbia, but also includes Puerto Rico, the US Virgin Islands, and Guam. We were able to obtain the data series without the costs for these three places, as needed for comparability with the US national accounts, for which we thank Adam B. Smith of NOAA. For the most part, the inclusion of these three areas, only appearing in four years, does not have an impact. However, one of those years includes Hurricane Maria, which had devastating impacts on Puerto Rico and the US Virgin Islands, and in that year the new data series records a difference of $125.4 billion. This series, which we use throughout, is referred to as NOAA disaster costs.

The first column in Table 2 shows the number of NOAA disaster events, where billion-dollar events are measured in constant dollars (using the CPI) of the latest year for which data are available, in this case 2023.[3] The number of billion-dollar events has been rising steadily: In the decade from 1980 to 1989, NOAA recorded a yearly average of 3.3 events that cost a billion dollars or more, using the prices of 2023. By comparison, from 2014 to 2023, there were 17.0 such events a year.

As time has passed, more past events have qualified as billion-dollar disasters because the CPI has risen over time and, in turn, the value of a billion dollars becomes smaller relative to the past. In 1980, for example, originally there was only one disaster greater than $1 billion: a $10 billion drought and heat wave in the summer and fall. Now, measured in 2023 dollars the drought and heat wave event is reckoned at $39.7 billion, and there are three events that qualify. NOAA collected events in the data set that originally cost less than one-third of a billion dollars,

[3] Specifically, February 2023 is set to 1.00 for deflation adjustment.

but this does open up the possibility that some small events may have been missed in the 1980s now that the CPI deflator raises the cost of events nearly fourfold.[4] It might be preferable to have the cutoff be a constant proportion of GDP but the NOAA methodology permits recalculation as needed.

The second column in Table 2 shows the aggregate time series of NOAA costs covering the period from 1980 to 2023, as communicated privately by Adam Smith of NOAA. in March 2024. Figure 1 depicts graphically that, in the period from 1980 to 2000, there are no years with total real disaster costs greater than $100 billion, while there are seven such years from 2001 to 2022. Figure 1 and column 3 in Table 2 show the centered ten-year moving average of BWCD costs. The losses are irregular enough that the moving average does not rise monotonically and shows long periods of non-increase, although each decade does rise monotonically, as we see in Table 3. In the decade from 1980 to 1989, the average annual BWCD cost is $21.1 billion, while in the decade from 2014 to 2023, the average annual BWCD cost is $108.9 billion, a real compound annual growth rate of 4.8 percent.

As part of the US National Income Accounts, the BEA makes rough estimates of the costs of disasters that are larger than 0.1 percent of GDP, as part of published Other Changes in the Volume of Assets (both disaster costs and OCVA are by convention positive when they subtract from assets). These rough estimates differ from the NOAA estimates both in using a higher cutoff point (0.1 percent of GDP in 2022 was $25.7 billion, substantially larger than the $1 billion cutoff in BWCD) and in the less systematic way they are collected.[5] These data are

[4] NOAA has a project underway to detect and include even smaller disasters now and going back to 1980.
[5] Private communication with Robert Kornfeld: "There is no standard source for these extremely rough estimates of catastrophic losses. We use reports from insurance companies and associations, other financial institutions, FEMA, other federal and state and local government agencies, even newspaper articles."

shown in column 4 of Table 2. Such events remain relatively rare; 23 of the 43 years have zero values.

Disasters make up 99 percent of all OCVA. We show these data in Figure 2, where we deflate both NOAA and BEA disasters with the CPI, in 2023 dollars. Notice that the cost of BEA's disasters is less than NOAA's, except in 1994 (Northridge earthquake) and 2001 (9/11 terrorist attacks) when disasters were not due to weather or climate. All told, BEA's disasters sum to $802 billion (in 2023 dollars, deflated by the CPI-U) or 31.8 percent the size of NOAA's $2,524 billion over this period from 1980 to 2023.

Ideally, NOAA would differentiate between asset and non-asset costs, but they do not do so now. To approximate what the data would look like if we had those data, we could extend BEA's data to include smaller events found in NOAA, by using NOAA data on small events to extrapolate. Alternatively, we would like to remove the non-asset costs from NOAA data, using BEA data on large events to extrapolate (the two methods achieve the same result).

Table 2 shows that there are also some BEA disasters that are below 0.1 percent of GDP; these originated before the 2008 change in methodology and reflect the time when disasters were included in CFC and disaster collection was less truncated. We can easily remove these small disasters and the two non-weather-and-climate disasters. Then the remaining disasters in BEA costs constitute truncated, noisy observations on the same events as NOAA's, except that NOAA's data include non-asset costs. These are shown in Table 4 and represent our lower bounds on weather-and-climate-disaster asset costs. We now have upper and lower bounds.

To come up with a single best estimate, we could form a weighted average of the two upper and lower bounds, but what should the weights be? One possibility would be to give equal weights and average the two. We call this the midpoint hypothesis. Is it plausible? Since BEA data are about 32 percent of NOAA's, taking the midpoint would be 66 percent of the NOAA costs (the average of NOAA and BEA is \$1,663 billion in 2023 dollars). That would imply that the truncation removes slightly more than half of all the disaster asset losses in the BEA data, relative to the NOAA data set. Alternatively, these same numbers suggest that roughly one-third of NOAA costs are non-asset costs.

To investigate the plausibility of midpoint weighting, let's call BEA's weather and climate truncated observations $B_i = A_i$ when A > .001 GDP, and NOAA's observations $N_i = A_i + C_i$, where A are asset costs and C are non-asset costs. Let us also use the notation that GDP at the time of event i is GDP_i where i stands in for the date at which event i is observed, and i runs from 1 to I. We will also assume here that by definition a relevant event is at least \$1 billion in real terms, to avoid fussy notation. Ts will indicate sums.

To begin, let the BEA observations sum to BT*. $BT^* = \sum_1^I A_i | A_i \geq .001\ GDP_i$. We would like to know $BT - \ BT^* = \sum_1^I A_i | A_i < .001\ GDP_i$. If we did, we would have $\sum_1^I A_i$. Similarly, the NOAA observations sum to $NT = \sum_1^I A_i + C_i$= \$2524. If we knew $CT = \sum_1^I C_i$, we could have another estimate of $\sum_1^I A_i$. We are going to assume that the ratio of BT* to $NT^*(= \sum_1^I A_i | A_i \geq .001\ GDP_i)$ is the same as for the ratio of BT to NT. If this proportion is 1 to 1+c, where c is some constant, then NT* = 1+c)BT* and NT = (1+c)BT. Then c = NT/BT-1.

Let us consider the ratio of NT_c*/BT* where $NT_c^* = \sum_1^I A_i + C_i | A_i \geq .001\ (1 + c)\ GDP$. As c gets larger, this ratio shrinks. When c = -1, NT_c* = NT, which is larger than BT*. And for c large enough, NT_c* = 0, since no events qualify. So, if NT_c* were continuous, there would be a fixed point at which c would satisfy the equation, c = NT_c*/BT*-1. Although NT_c* are not continuous, we can hope for an approximate solution. The midpoint hypothesis is that c = .5 roughly. $NT_{.5}^* = \sum_1^I A_i + C_i | A_i \geq .0015\ GDP$. Does this satisfy the equation .5 = $NT_{.5}$*/BT*-1?

The BEA events, once we have trimmed off the two non-weather events and the events smaller than 0.1 percent of GDP, sum to \$692.1 billion (in 2023 dollars); this is BT*. The data can be found in Table 4, column 1. If we take all the NOAA events that are greater than .0015 GDP, they sum to \$1,023.6 billion (in 2023 dollars); see Table 4, column 2. This is our estimate of $NT_{.5}$*. $NT_{.5}$*/BT*-1 = 1024/692-1= .48 = c. This tends to confirm the validity of taking the midpoint; we have found an approximate fixed point.

An alternative way to look at this is to ask whether large BEA weather and climate events are associated with the NOAA events greater than .015 GDP, and vice versa. In fact, some Ns will be between .001 GDP and .015 GDP when A is greater than .001 (type 1 errors), and some Cs will produce Ns that are greater than .015 GDP when A is less than .01 GDP (type 2 errors). Hopefully these will approximately counterbalance one another.

Looking at Table 4 year by year, we see broadly that, where we see a BEA disaster cost, these are matched with larger costs in the NOAA large disaster costs. There are two type 1 errors, one in 2004 and one in 2018, when there are BEA disaster costs with no corresponding NOAA costs. In 2004, there is a NOAA event that is greater than .001 GDP but less than .015 GDP, and in 2018, there are three such events. On the other hand, there are two years, 1880 and 1888, with type 2 errors, where we observe large NOAA disaster costs with no comparable BEA disaster costs. In these two cases, the events are droughts and heat waves that likely had large non-asset costs (primarily crop losses). Balancing out the errors gives us some confidence that this analysis has some merit. We therefore will use the midpoint as our preferred measure of capital costs of disasters. On the other hand, while the midpoint is very useful as a crude approximation for the trend, on a year-by-year basis the resulting series is evidently far off in some cases, as the two types of errors in four years discussed above make evident.

We have leaned very heavily on the assumption here that large asset events have a similar ratio to non-asset costs as do small ones; it would be much better to have measures of NOAA costs divided up into asset and non-asset costs.

In creating our midpoint data, we use the published BEA disaster data, leaving in the smaller disasters and the non-weather-and-climate disasters. This is done because the National Accounts disaster data series should include all asset disasters, not just weather and climate disasters. The extent of depreciation is not affected by the source of the disasters. Therefore, we take the midpoint of the NOAA disaster costs and BEA disaster costs. We acknowledge that it might be more accurate to take the full value of the two BEA non-weather-and-climate disasters (1994 and 2001) into the midpoint series rather than take half of it, as we know they are not included in the NOAA data. Another alternative would be to focus on weather and climate disasters and omit the two non-weather-and-climate disasters. We prefer to use the simple midpoint as an approximation that emphasizes the crudeness of this approach.

V. Measuring Expected Costs

We now turn to the estimation of the expected component of NOAA costs and BEA costs to guide an experimental measurement of Consumption of Fixed Capital. In what follows, the NOAA costs will be the first object of interest, although these data overestimate asset costs because the data are so much more complete and richer. We do a simple analysis of the trend in BEA costs. An estimate of capital losses that combines the trend in BWCD costs and in BEA costs will then be constructed using the midpoint estimates we have just discussed as our best estimate of asset disaster costs.

Measurement of trend in NOAA costs.

Our proposed method uses a log trend to estimate expected NOAA costs and proposes to add these expectations to Consumption of Fixed Capital. To estimate this expectation, we use two types of regressions. The first is a conventional OLS regression of log NOAA costs (N) on time:

$$\ln(N_t) = a + b\ time + \varepsilon_t.$$

The second is a Poisson pseudo-maximum-likelihood regression on time:

$$N_t = \exp(a + b\ time) + \varepsilon_t.$$

OLS regression of log annual NOAA costs on time.

The first regression of log losses can be used to capture the exponential trend growth, but there were no billion-dollar disasters in 1987 and the log of zero does not exist, so we need to either add a dummy variable for that date or replace the zero with 1, whose log is zero, an approximation often used empirically. The dummy variable will tend to bias down the growth rate (because it in effect replaces an unusually small early number with an average value), so that will be our preferred regression as it is the most conservative. The output of the OLS regression with a 1 inserted in 1987 costs (so that the log is zero) is shown in Table 5, column 1, which gives a trend growth rate of 5.8 percent annually. The output of the OLS regression with a dummy variable included for 1987 is shown in Table 5, column 2. This gives a trend growth rate of 5.2 percent annually.

One difficulty of using the log trendline is that the error term is then in logs. Logs take arithmetically large positive errors and reduce them relative to negative errors.[6] This issue is

[6] The usual fix is to add half the regression variance to the mean that is being exponentiated, which is strictly valid only when the logged random variable is distributed lognormally. Duan's (1983) nonparametric smearing transformation would apply beyond the lognormal case and has been used by health econometricians.

discussed in Santos Silva and Tenreyro (2006), who argue, in the context of the gravity equation for trade, that since Jensen's inequality implies that $E(\ln y) \neq \ln E(y)$ the first regression in the presence of heteroskedasticity is not just inefficient but biased. They suggest using Poisson pseudo-maximum-likelihood estimation techniques to estimate the exponential regression.[7]

Regression of NOAA costs on exponential of time using Poisson pseudo-maximum-likelihood estimation technique.

The first advantage of using the Poisson regression rather than the log OLS regression for this data is that there is no concern about the zero costs in 1987. Another is that the estimation will not be biased; we are attempting to find the trend for costs, not the log of costs. A third is that the Poisson pseudo-maximum-likelihood regression is tolerant of error misspecification.

We used the Poisson command in Stata to generate our preferred measure of expected NOAA costs, with output shown in Table 5, column 3. The trend growth rate is 4.9 percent, a lower trend than the two previous regressions.

Figure 3 depicts our two measures of expected cost in comparison to actual costs. Figure 4 shows them with the ten-year moving averages of costs. The log trend is below the Poisson trend as we would expect from the Santos Silva and Tenreyro argument. In addition, the Poisson trend traces the moving average much more closely than the conservative log trend. The robust standard errors of the two regressions show that the Poisson trend is measured somewhat more precisely than the log regressions; we interpret this as a modest win for our preferred measure.

Regression of BEA disaster costs on time using Poisson pseudo-maximum likelihood.

[7] See Gourieroux, Monfort, and Trognon (1984) for the original work, and Santos Silva and Tenreyro (2006), who implement the Poisson pseudo-maximum likelihood in a trade setting after considering some related alternatives. This point has been made in the context of these losses by Smith and Katz (2013).

Similarly, we can use the Poisson regression to analyze the time trend in the BEA measure of asset disaster costs as part of OCVA. The resulting output with robust errors is shown in Table 5, column 4. The trend growth rate is 4.8 percent, very close to that in the Poisson regression on NOAA costs. We have not performed an OLS log regression using BEA disaster costs, since there are 20 zeroes in the 43 observations, so results would scarcely be meaningful.

We can interpret the NOAA data as creating an upper bound on asset disaster costs since they include costs that are short run and not capital costs. We interpret the BEA data as creating a lower bound on asset disaster costs. We have shown that it is plausible to treat the midpoint of the data (that is, the average of the two) as a best approximation to asset costs. The result of taking a Poisson trend on the midpoint is shown in Table 5, column 5. This is equivalent to taking the average of the two separate trends. The coefficient on time shows a trend of 4.9 percent.[8]

The numerical costs and trends are shown in Table 6. The first two columns are NOAA disaster costs and trends and the next two are BEA asset disaster costs and trends. Our preferred measures of asset disaster costs, trends, and residuals are shown in the final three columns. Our view is that the trend of disaster asset costs should be included in Consumption of Fixed Capital, and the residual actual costs less the trend should be included in Other Changes in the Volume of Assets. In particular, we have argued that the midpoint trend and the midpoint costs are the best estimate of these asset costs and should be so included. These real data here are deflated by the CPI-U, but for the National Income Accounts the relevant prices should be the replacement costs of the assets as is true for other components of CFC and OCVA.

[8] As discussed at the end of Section IV, it might be more accurate to use the full unit weight of the non-weather-and-climate disasters of the BEA disaster data that we are aware of. Doing so gives a Poisson regression with a constant of 2.42 and a slightly lower time coefficient of .0472.

Our argument is that the needs of the national accounts with rising climate disaster costs will be best served by adding something like the midpoint cost trend to Consumption of Fixed Capital and placing the residuals from the disasters in Other Changes in the Volume of Assets, as shown in the final two columns of Table 5. Note that the residuals can be of either sign and by construction sum to zero; this contrasts with the current treatment in which OCVA is invariably positive. Remember as well that these annual movements in OCVA contain substantial errors, as noted earlier.

Further exploration of the methodology is warranted and is pursued in the Appendix for robustness, using the slightly less accurate Billion-Dollar Weather and Climate Disasters costs in official NOAA data published in 2023. The alternative approach used there is to first investigate the distribution of the *average* annual costs, that is, per event, which are shown to be trendless. The most probable distributions are seen to not be fat-tailed. Here we deal with the zero in 1987 by assuming that the data are truncated; over time we would expect a positive value to appear in 1987 as the base year of the CPI moves along. The trend in the total *annual* costs is similar to that found using the Poisson methodology on the same data set. This trend in the annual costs leads to a distribution that allows for larger tail values over time.

To compare the impact of the trend on CFC and NDP, Table 7 provides measures in nominal terms. We use nominals because of the inaccuracy that would be introduced by, for example, using the CFC overall deflator to deflate our measures of asset disaster costs and trends. Nominal disaster costs and the trend measure are constructed by reflating the real data using the CPI-U after setting the CPI-U to a February 2023 base of 100.

If we view the trendline as the expected loss, then these expected losses have risen from 0.12 percent of NDP to 0.40 percent. If we were to subtract these from NDP, the effect for the 44 years would be to decrease the annual growth rate of NDP by 0.007 percentage points, in nominal terms from 5.205 to 5.198 percent.

The impact on the overall rate of depreciation is more noticeable. Without including the midpoint trend, Consumption of Fixed Capital as a proportion of NDP goes from 17.6 percent in 1980 to 20.2 percent in 2022. Including the trend in the asset disaster trend, CFC as a proportion of NDP is 17.9 percent in 1980 and 20.5 precent in 2023. The asset disaster trend, as a proportion of CFC, rises from 0.7 to 2.0 percent.

Pre-2009 method, including climate catastrophes in NDP without smoothing.

GDP and NDP are ex post measures. Using expectations and smoothing trendlines is not necessarily the best way of capturing outcomes. In this spirit, as discussed earlier, the unsmoothed large disaster losses used to be added to CFC and thus subtracted from NDP. This perhaps better captured the welfare impact of disasters but at the cost of introducing a substantial amount of noise into measures of NDP that are unrelated directly to production and would thus weaken its relationship to other economic variables, such as employment. This is not in the general spirit of production accounting, and it thus might be preferable to include these shocks into an account such as Expanded GDP (Hulten and Nakamura, 2022) designed to better capture welfare.

Column 6 in Table 7 shows disaster costs as a percentage of annual NDP. It can be seen that these have a visible impact on NDP. In 2017, disaster costs were 1.0 percent of NDP, following on 0.2 percent of NDP the previous year. The difference of 0.8 percentage points would likely have reduced real NDP 2017 growth from 2.3 to 1.5 percent. This slow growth rate may have better reflected the change in well-being in that year of dreadful storms and fires than the current or our proposed methodology. The counterpart would have been a much higher growth rate from 2017 to 2018.

The largest impact of the increase in CFC would be on NDI, the result of subtracting CFC from Gross Domestic Investment, which represents the extent to which the domestic capital stock is augmented annually. Table 8 shows decade averages of NDI as currently published, the disaster trend, and the percent impact of the disaster trend on NDI in nominal terms under our proposed treatment. From 1980 to 1989, the correction lowers NDI by 1.4 percent; from 2014 to 2023, NDI is lower by 6.2 percent. In 2023, the correction is 7 percent.

Further exploration of asset disaster data might include disaggregating to the seven disaster-type categories that comprise them, experimenting with different but more apt deflators than the CPI for depreciation purposes, and perhaps replacing time as the trend-driver with some measure of climate change.

VI. Summary

In brief, in this paper we outline a new proposed method for adjusting Consumption of Fixed Capital for catastrophic climate losses to make more visible the rising impact of these losses in NDP. The proposed measure has a small impact on the growth rate of NDP but reduces NDP's level by 0.4 percent. The method used prior to 2009 can have substantial impacts on the year-to-year growth of NDP. Our empirical implementation reflects two sources of weather-related costs, from NOAA and BEA, and these form an upper and lower bound on the measure we seek. We propose taking the midpoint of trends as our best estimate. The underlying data from NOAA could use further work to remove some climate and disaster costs that are not asset costs to facilitate their use in the US National Income and Product Accounts. In the meantime, these estimates are necessarily crude.

In addition, it would eventually be desirable to disaggregate the data broadly, by type of asset and by region. Disaggregation by type of asset is important for accurate deflation of costs of BWCD and its trend. Regional depreciation is generally not performed despite its potential usefulness in regional measures.

We have taken three statistical approaches to the trend in NOAA data: a log-linear time trend with a dummy, a Poisson pseudo-maximum-likelihood approach, and a parametric approach that accounts for truncation. With the sparser data from BEA we only used the Poisson regression. We find a real trend of 4.9 percent annually for our preferred regression, which uses the midpoint of BEA and NOAA data.

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Table 1. Schematic Design of Past and Proposed National Accounts Treatment of Disasters		
Period	Consumption of Fixed Capital includes:	Other Changes in the Volume of Assets includes:
Pre-2009 treatment	Disaster Trend and Disaster Residuals	Not Applicable
Current treatment	No part of Disasters	Disaster Trend and Disaster Residuals
Proposed treatment	Disaster Trend	Disaster Residuals

Table 2. Annual US Disasters as Measured by NOAA and BEA (billions of 2023 US dollars, deflated by CPI-U)					
Year	(1) Number of NOAA Disasters	(2) NOAA Disasters Cost	(3) 10-Yr Moving Average of NOAA Disasters Cost	(4) BEA Disasters Cost	(5) 10-Yr Moving Average of BEA Disasters Cost
1980	3	44.6		1.8	
1981	2	3.4		0.0	
1982	3	5.3		2.8	
1983	6	35.5		3.3	
1984	2	3.1		0.0	
1985	7	22.0	21.1	4.8	3.5
1986	3	7.7	18.0	0.0	3.3
1987	0	0.0	19.6	0.0	3.6
1988	1	53.4	26.9	0.0	7.2
1989	6	35.6	29.8	21.9	7.7
1990	4	14.2	31.1	0.0	11.8
1991	4	19.2	31.9	3.3	11.8
1992	7	78.2	33.4	38.5	11.8
1993	5	64.2	34.9	8.6	11.8
1994	6	16.3	32.7	41.5	11.8
1995	6	30.4	31.5	4.7	10.3
1996	5	22.7	31.6	0.0	10.3
1997	3	14.9	31.8	0.0	13.2
1998	11	31.4	26.7	0.0	9.4
1999	5	23.9	24.0	6.3	8.5
2000	5	15.1	31.3	0.0	9.1
2001	3	21.3	54.5	32.7	26.4
2002	6	26.6	54.7	0.0	26.4
2003	7	37.6	55.0	0.0	26.4
2004	6	89.3	61.1	46.9	29.0
2005	6	262.2	60.6	177.7	28.4
2006	8	24.7	61.1	0.0	28.4
2007	5	18.4	68.6	0.0	25.1
2008	12	91.9	81.4	26.8	31.1
2009	9	19.3	80.8	0.0	31.1
2010	7	19.7	74.4	0.0	26.4
2011	18	95.9	51.2	0.0	8.7

2012	11	155.3	54.8	60.0	8.7
2013	10	31.6	79.1	0.0	21.5
2014	10	25.0	81.2	0.0	25.0
2015	11	30.3	84.7	0.0	25.0
2016	15	60.1	94.6	0.0	25.0
2017	18	261.4	101.1	128.0	31.9
2018	16	113.5	103.2	61.5	32.0
2019	14	54.3	108.9	0.0	32.0
2020	22	118.2		0.0	
2021	20	160.8		69.0	
2022	17	176.5		61.8	
2023	27	88.8		0.0	
Total	372	2523.8		802.0	

Sources: NOAA National Centers for Environmental Information (2024); private communication with Adam Smith of NOAA; Haver; authors' calculations.

Table 3. Decade Averages of NOAA Disaster Events and Costs, and BEA Disaster Costs (billions of 2023 US dollars, deflated by CPI-U)				
	(1)	(2)	(3)	(4)
Decade	Number of NOAA Disasters	NOAA Disasters Cost	Cost per NOAA Disaster	BEA Disaster Costs
1980–89	3.3	21.1	6.4	3.5
1990–99	5.6	31.5	5.6	10.3
2000–09	6.7	60.6	9.1	28.4
2010–19	3.0	84.7	6.5	25.0
2014–23	17.0	108.9	6.4	32.0

Sources: NOAA National Centers for Environmental Information (2024); private communication with Adam Smith of NOAA; Haver; authors' calculations.

Table 4. Large BEA and NOAA Events: BEA Events Exceeding .001 Times GDP and NOAA Events Exceeding .0015 Times GDP (billions of 2023 US dollars, deflated by CPI-U)		
Year	BEA Disaster Costs	NOAA Disaster Costs
1980		39.7
1988		53.4
1989	21.9	22.2
1992	38.5	59.1
2004	46.9	33.2
2005	177.7	196.3
2008	26.8	42.3
2012	60.0	127.3
2017	128.0	205.9
2018	61.5	
2021	69.0	83.1
2022	61.8	116.3
Total	692.1	1024.1

Sources: NOAA National Centers for Environmental Information (2024); private communication with Adam Smith of NOAA; Haver; authors' calculations.

Table 5. Coefficients of Time in Trend Regressions on Disaster Costs					
	(1)	(2)	(3)	(4)	(5)
Disaster Costs Source	NOAA	NOAA	NOAA	BEA	Midpoint BEA and NOAA
Regression Type	OLS	OLS	Poisson	Poisson	Poisson
Constant St. err (prob)	2.199 .343 (.000)	2.392 .304 (.000)	2.747 .284 (.000)	1.64 .555 (.003)	2.33 .322 (.000)
Time St. err. (prob)	.0576 .0116 (.000)	.0518 .0107 (.000)	.0494 .0085 (.000)	.0481 .0165 (.004)	.0491 .0097 (.000)
Dummy for 1987	No	Yes	No	No	No
1987 cost =1	Yes	Yes	No	No	No
Columns 1 and 2 are OLS regressions of log BWCD costs on time with a constant. Column 1 substitutes log BWCD(1987) = 0. Column 2 adds a dummy for the year 1987. Column 3 is the Poisson pseudo-maximum-likelihood regression of BWCD costs on time. Column 4 is the Poisson pseudo-maximum-likelihood regression of BEA costs on time. Standard errors are robust. Results for non-robust standard errors are tighter and for bootstraps somewhat looser but all are better than .013 percent and available upon request.					

Sources: NOAA National Centers for Environmental Information (2024); private communication with Adam Smith of NOAA; Haver; authors' calculations.

Table 6. BEA and NOAA Disaster Costs with Trends Based on Poisson Trend Regressions (billions of 2023 US Dollars, deflated by CPI-U)							
Year	Total NOAA Costs	NOAA Trend	Total BEA Costs	BEA Trend	Disaster (Midpoint) Costs	Disaster Trend: To CFC	Disaster Residual: To OCVA
1980	44.6	16.4	1.8	5.4	23.2	10.9	12.32
1981	3.4	17.2	0.0	5.7	1.7	11.4	-9.75
1982	5.3	18.1	2.8	6.0	4.1	12.0	-7.97
1983	35.5	19.0	3.3	6.3	19.4	12.6	6.79
1984	3.1	20.0	0.0	6.6	1.6	13.3	-11.71
1985	22.0	21.0	4.8	6.9	13.4	13.9	-0.55
1986	7.7	22.0	0.0	7.2	3.9	14.6	-10.78
1987	0.0	23.2	0.0	7.6	0.0	15.4	-15.37
1988	53.4	24.3	0.0	8.0	26.7	16.1	10.56
1989	35.6	25.6	21.9	8.3	28.7	17.0	11.79
1990	14.2	26.9	0.0	8.8	7.1	17.8	-10.71
1991	19.2	28.2	3.3	9.2	11.3	18.7	-7.45
1992	78.2	29.7	38.5	9.6	58.3	19.6	38.68
1993	64.2	31.2	8.6	10.1	36.4	20.6	15.74
1994	16.3	32.7	41.5	10.6	28.9	21.7	7.22
1995	30.4	34.4	4.7	11.1	17.6	22.8	-5.18
1996	22.7	36.1	0.0	11.7	11.4	23.9	-12.56
1997	14.9	38.0	0.0	12.3	7.5	25.1	-17.67
1998	31.4	39.9	0.0	12.9	15.7	26.4	-10.69
1999	23.9	41.9	6.3	13.5	15.1	27.7	-12.59
2000	15.1	44.0	0.0	14.2	7.6	29.1	-21.56
2001	21.3	46.3	32.7	14.9	27.0	30.6	-3.57
2002	26.6	48.6	0.0	15.6	13.3	32.1	-18.81
2003	37.6	51.1	0.0	16.4	18.8	33.7	-14.93
2004	89.3	53.7	46.9	17.2	68.1	35.4	32.67
2005	262.2	56.4	177.7	18.0	220.0	37.2	182.75
2006	24.7	59.3	0.0	18.9	12.4	39.1	-26.73
2007	18.4	62.3	0.0	19.8	9.2	41.0	-31.85
2008	91.9	65.4	26.8	20.8	59.3	43.1	16.21
2009	19.3	68.7	0.0	21.8	9.7	45.3	-35.64
2010	19.7	72.2	0.0	22.9	9.9	47.6	-37.72
2011	95.9	75.9	0.0	24.0	48.0	50.0	-2.01
2012	155.3	79.7	60.0	25.2	107.7	52.5	55.18
2013	31.6	83.8	0.0	26.5	15.8	55.1	-39.32
2014	25.0	88.0	0.0	27.8	12.5	57.9	-45.40
2015	30.3	92.5	0.0	29.1	15.2	60.8	-45.66
2016	60.1	97.2	0.0	30.6	30.1	63.9	-33.82
2017	261.4	102.1	128.0	32.1	194.7	67.1	127.65

2018	113.5	107.3	61.5	33.7	87.5	70.5	17.02
2019	54.3	112.7	0.0	35.3	27.1	74.0	-46.88
2020	118.2	118.4	0.0	37.1	59.1	77.7	-18.64
2021	160.8	124.4	69.0	38.9	114.9	81.7	33.24
2022	176.5	130.7	61.8	40.8	119.1	85.8	33.38
2023	88.8	137.4	0.0	42.8	44.4	90.1	-45.69

Sources: NOAA National Centers for Environmental Information (2024); private communication with Adam Smith of NOAA; Haver; authors' calculations.

Table 7. Impact of Costs and Trend of Including Billion-Dollar Weather and Climate Disasters in Consumption of Fixed Capital, in Nominal Terms									
	Billions of Dollars				Percent of Net Domestic Product				
Year	(1) NDP	(2) CFC	(3) Disaster Costs	(4) Disaster Trend	(5) Disaster Costs	(6) Disaster Trend	(7) CFC	(8) CFC + Costs	(9) CFC + Trend
1980	2428.9	428.4	6.3	3.0	0.26%	0.12%	17.6%	17.9%	17.8%
1981	2719.8	487.2	0.5	3.5	0.02%	0.13%	17.9%	17.9%	18.0%
1982	2806.8	537.0	1.3	3.8	0.05%	0.14%	19.1%	19.2%	19.3%
1983	3071.4	562.6	6.4	4.2	0.21%	0.14%	18.3%	18.5%	18.5%
1984	3439.2	598.4	0.5	4.6	0.02%	0.13%	17.4%	17.4%	17.5%
1985	3698.8	640.1	4.8	5.0	0.13%	0.13%	17.3%	17.4%	17.4%
1986	3894.3	685.3	1.4	5.3	0.04%	0.14%	17.6%	17.6%	17.7%
1987	4124.8	730.4	0.0	5.8	0.00%	0.14%	17.7%	17.7%	17.8%
1988	4451.9	784.5	10.5	6.3	0.24%	0.14%	17.6%	17.9%	17.8%
1989	4803.3	838.3	11.8	7.0	0.25%	0.15%	17.5%	17.7%	17.6%
1990	5074.6	888.5	3.1	7.7	0.06%	0.15%	17.5%	17.6%	17.7%
1991	5225.7	932.4	5.1	8.4	0.10%	0.16%	17.8%	17.9%	18.0%
1992	5560.1	960.2	27.1	9.1	0.49%	0.16%	17.3%	17.8%	17.4%
1993	5855.1	1003.5	17.4	9.9	0.30%	0.17%	17.1%	17.4%	17.3%
1994	6231.6	1055.6	14.2	10.7	0.23%	0.17%	16.9%	17.2%	17.1%
1995	6517.4	1122.4	8.9	11.5	0.14%	0.18%	17.2%	17.4%	17.4%
1996	6897.8	1175.3	5.9	12.4	0.09%	0.18%	17.0%	17.1%	17.2%
1997	7338.2	1239.3	4.0	13.4	0.05%	0.18%	16.9%	16.9%	17.1%
1998	7753.1	1309.7	8.5	14.3	0.11%	0.18%	16.9%	17.0%	17.1%
1999	8232.2	1398.9	8.4	15.3	0.10%	0.19%	17.0%	17.1%	17.2%
2000	8739.7	1511.2	4.3	16.6	0.05%	0.19%	17.3%	17.3%	17.5%
2001	8982.4	1599.5	15.9	18.0	0.18%	0.20%	17.8%	18.0%	18.0%
2002	9271.1	1658.0	7.9	19.2	0.09%	0.21%	17.9%	18.0%	18.1%
2003	9737.4	1719.1	11.5	20.6	0.12%	0.21%	17.7%	17.8%	17.9%
2004	10395.4	1821.8	42.7	22.2	0.41%	0.21%	17.5%	17.9%	17.7%
2005	11068.1	1971.1	142.5	24.1	1.29%	0.22%	17.8%	19.1%	18.0%
2006	11691.4	2124.2	8.3	26.1	0.07%	0.22%	18.2%	18.2%	18.4%
2007	12221.5	2252.8	6.3	28.2	0.05%	0.23%	18.4%	18.5%	18.7%
2008	12410.9	2359.0	42.4	30.8	0.34%	0.25%	19.0%	19.3%	19.3%
2009	12106.8	2371.3	6.9	32.2	0.06%	0.27%	19.6%	19.6%	19.9%
2010	12658.6	2390.4	7.1	34.4	0.06%	0.27%	18.9%	18.9%	19.2%
2011	13125.4	2474.4	35.8	37.3	0.27%	0.28%	18.9%	19.1%	19.1%
2012	13678.4	2575.5	82.0	40.0	0.60%	0.29%	18.8%	19.4%	19.1%
2013	14199.1	2681.6	12.2	42.6	0.09%	0.30%	18.9%	19.0%	19.2%
2014	14788.5	2819.7	9.8	45.5	0.07%	0.31%	19.1%	19.1%	19.4%

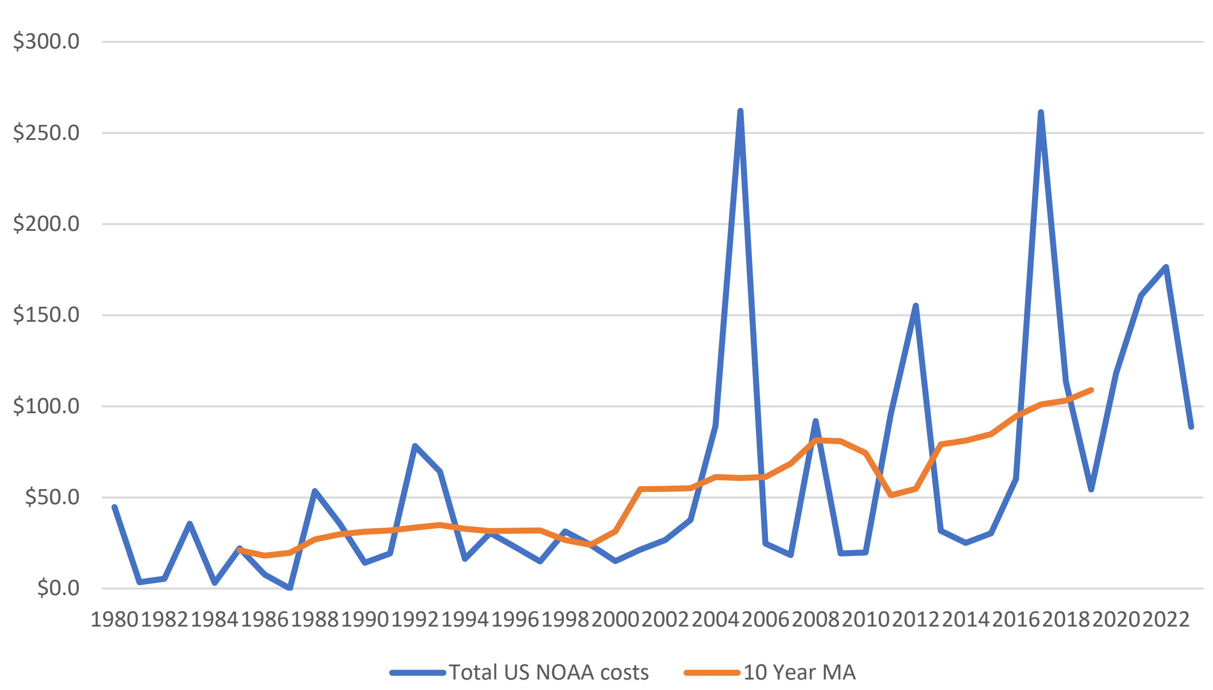
2015	15372.1	2922.9	11.9	47.8	0.08%	0.31%	19.0%	19.1%	19.3%
2016	15796.8	3008.1	23.9	50.8	0.15%	0.32%	19.0%	19.2%	19.4%
2017	16463.1	3149.0	158.3	54.5	0.96%	0.33%	19.1%	20.1%	19.5%
2018	17343.9	3312.6	72.9	58.7	0.42%	0.34%	19.1%	19.5%	19.4%
2019	18041.6	3479.8	23.0	62.8	0.13%	0.35%	19.3%	19.4%	19.6%
2020	17697.4	3625.5	50.7	66.7	0.29%	0.38%	20.5%	20.8%	20.9%
2021	19720.7	3873.3	103.3	73.4	0.52%	0.37%	19.6%	20.2%	20.0%
2022	21444.2	4299.9	115.6	83.2	0.54%	0.39%	20.1%	20.6%	20.4%
2023	22772.5	4585.4	44.9	91.0	0.20%	0.40%	20.1%	20.3%	20.5%
Growth rate	5.2%	5.5%	4.5%	8.0%					

Sources: NOAA National Centers for Environmental Information (2024); private communication with Adam Smith of NOAA; Haver; authors' calculations.

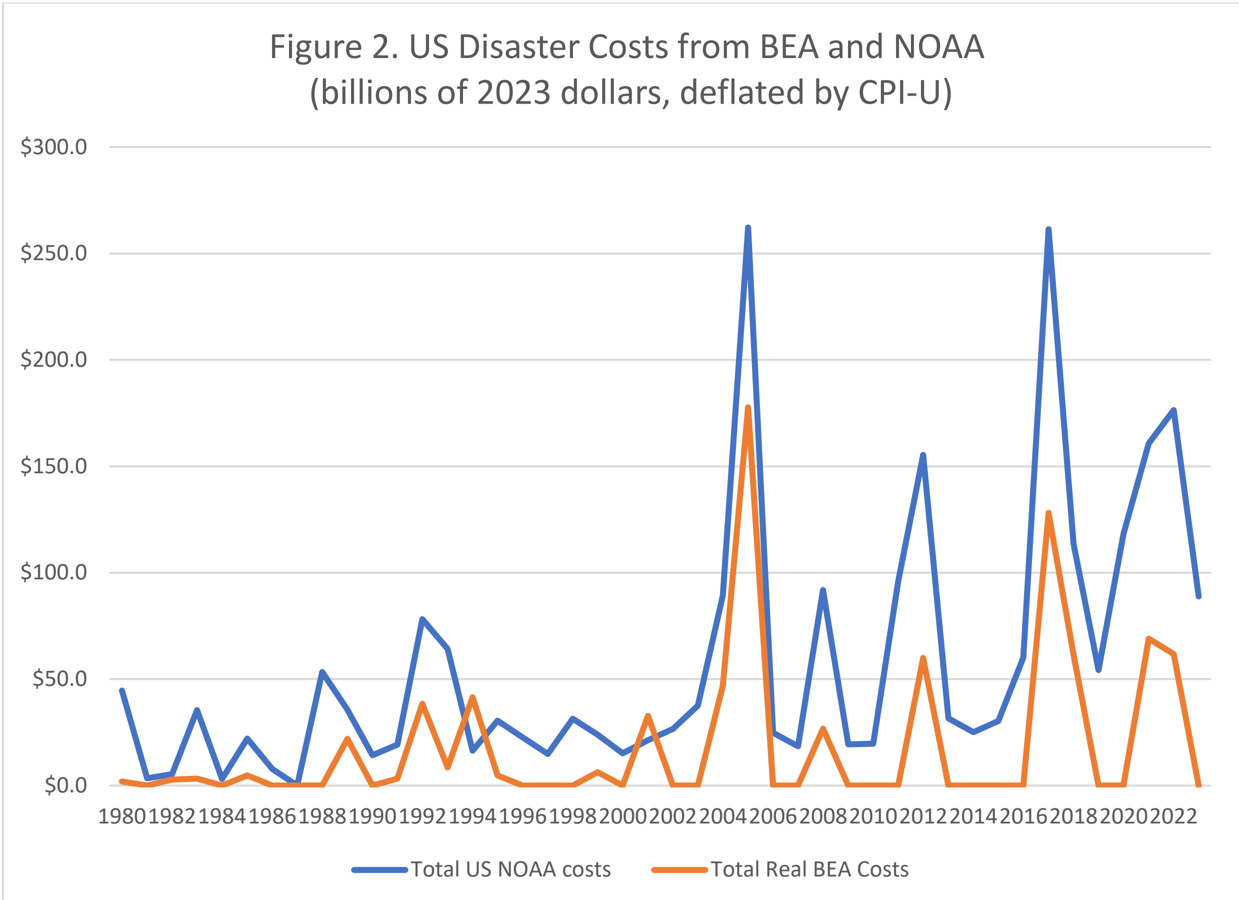
Table 8. Impact on Net Domestic Investment of Including Disaster Trend, 1980 to 2023 Decade Averages and 2023 Annual (billions of dollars, nominal)			
	Net Domestic Investment	Disaster Trend	Corrected Net Domestic Investment Reduction
1980–89	341.3	4.8	1.4%
1990–99	521.8	11.3	2.2%
2000–09	802.6	23.8	3.0%
2010–19	797.2	47.4	5.9%
2014–23	1016.5	63.4	6.2%
2023	1250.6	91.0	7.3%

Sources: NOAA National Centers for Environmental Information (2024); private communication with Adam Smith of NOAA; Haver; authors’ calculations.

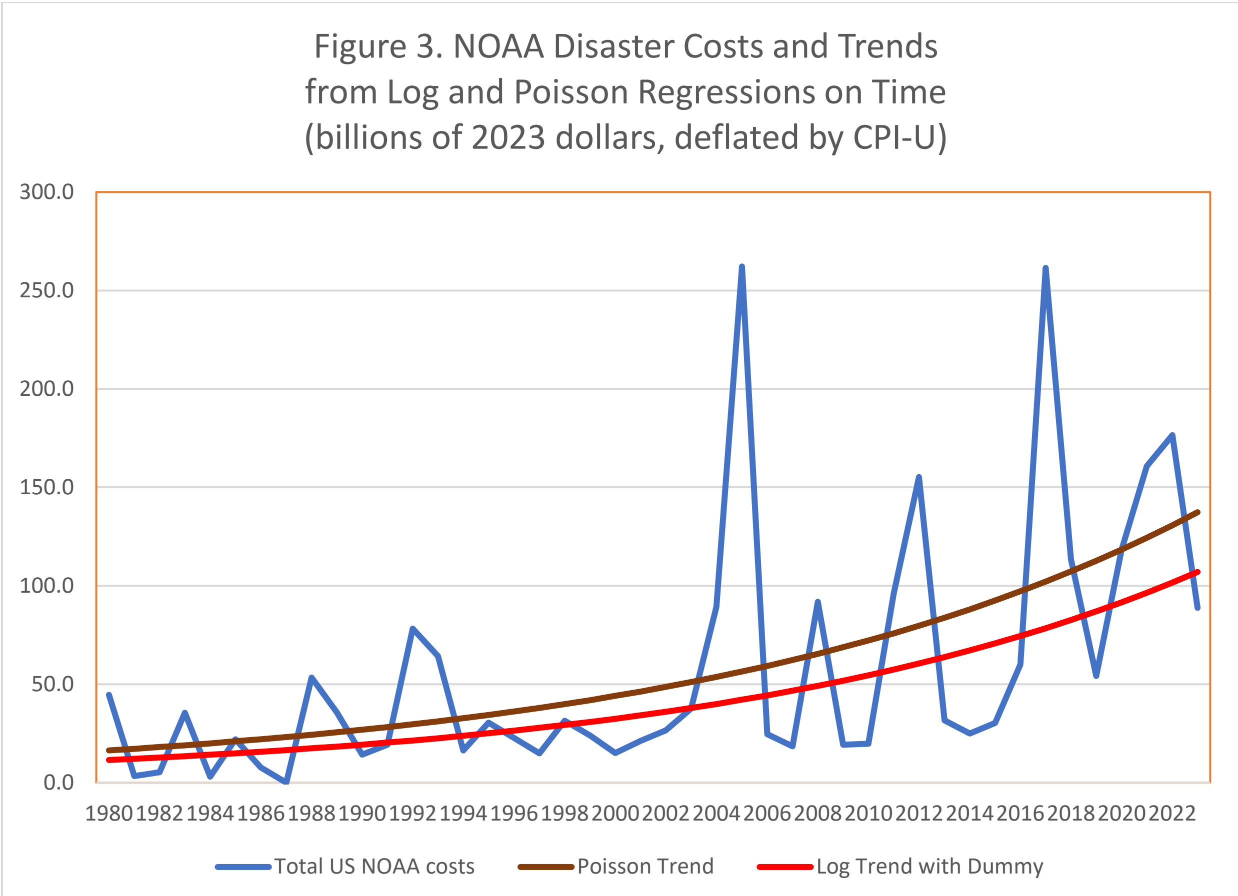
Figure 1. Real Billion-Dollar Weather and Climate Disasters from NOAA and 10-Year Centered Moving Average (billions of 2023 dollars, deflated by CPI-U)



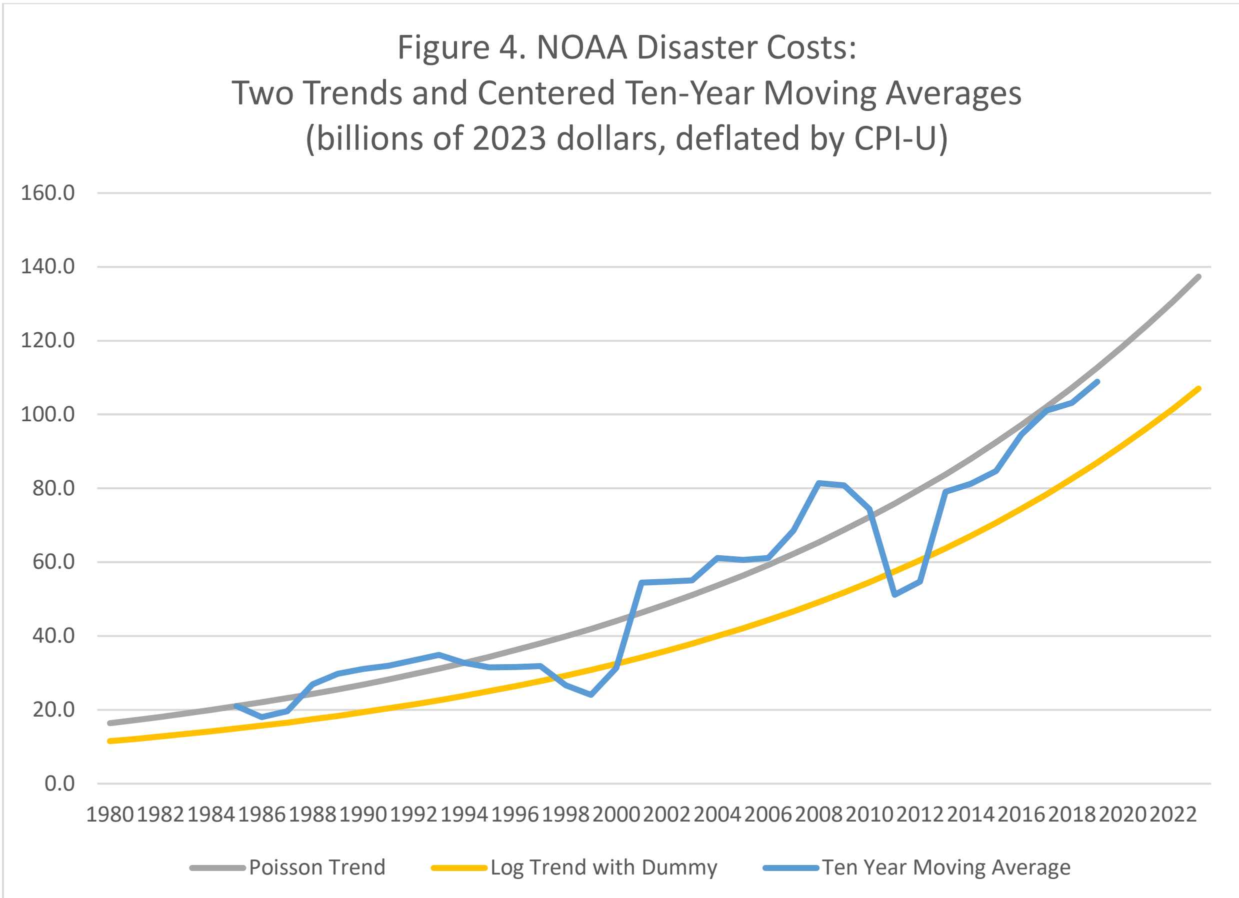
Sources: NOAA National Centers for Environmental Information (2024); private communication, Haver; authors' calculations.



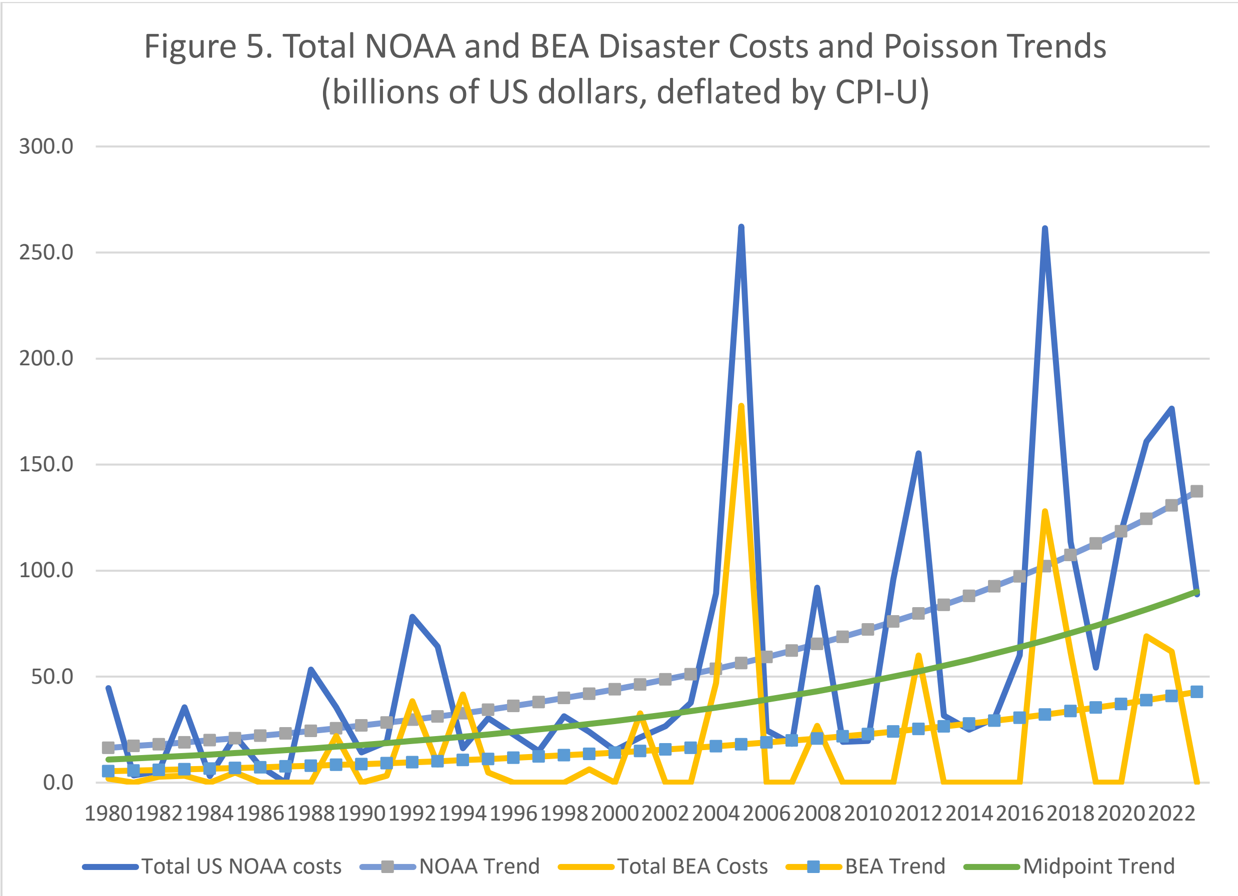
Sources: NOAA National Centers for Environmental Information (2024); private communication with Adam Smith of NOAA; Haver; authors' calculations.



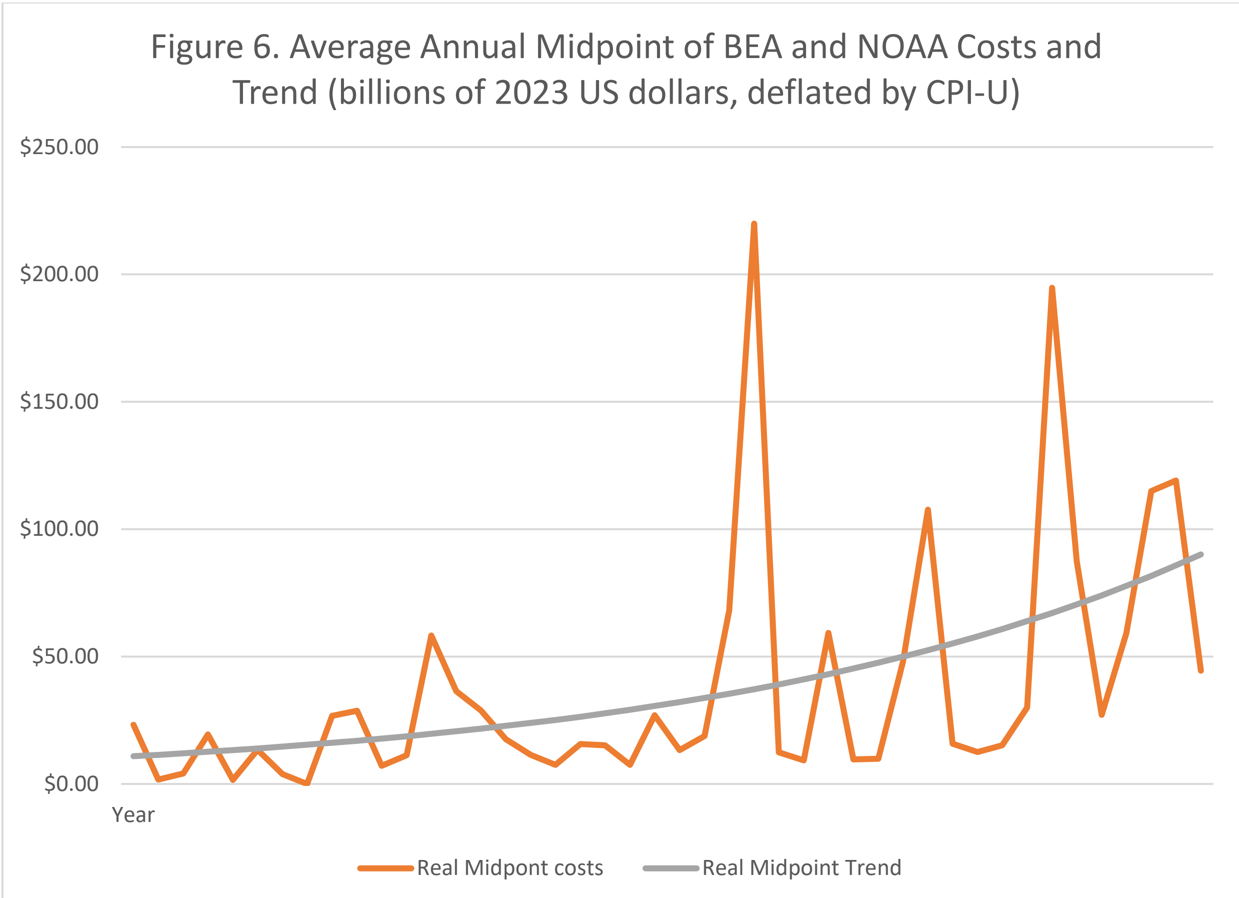
Sources: NOAA National Centers for Environmental Information (2024); private communication with Adam Smith of NOAA; Haver; authors' calculations.



Sources: NOAA National Centers for Environmental Information (2024); private communication with Adam Smith of NOAA; Haver; authors' calculations.



Sources: NOAA National Centers for Environmental Information (2024); private communication with Adam Smith of NOAA; Haver; authors' calculations.



Sources: NOAA National Centers for Environmental Information (2024); private communication with Adam Smith of NOAA; Haver; authors' calculations.

ONLINE APPENDIX

Alternative statistical approach to distributions and trend as a robustness check

Note: The following exercise was conducted with published NOAA Billion-Dollar Weather and Climate Disasters data collected in February 2023 that include NOAA climate costs from Puerto Rico, the US Virgin Islands, and Guam.

We can take a parametric approach to the problem of the zero for 1987 from the statistical perspective of truncation; that is, assume that there is some positive value of cost in 1987 but it has been truncated to zero[9] and that there is some parametric distribution from which the annual draws are being made. We begin by approaching the distributions that best describe the real *average* annual \$billion+ disaster-cost[10] and then move on to *total* \$billion+ disaster-cost series. The statistical approach explicitly accounts for left truncation (e.g., the absence of average-cost observations below \$1 billion or of total-cost observations below \$$k$ billion in years with k disasters in excess of \$1 billion). Finally, the choice of distribution might bear on Weitzman's (2009, 2011, 2014) apprehensions of thick-tailed climate risks.

We follow the well-worn path of estimating the distributions of average and total real disaster costs by maximum likelihood, testing a dozen more-or-less well-known two-parameter, right-skewed densities on the positive domain. These, with their parameters to be fit, are:

Beta Prime ($p>0$, $q>0$) Birnbaum-Saunders ($\alpha>0$, $\lambda>0$) Fréchet ($\beta>0$, $\theta>0$)

Gamma ($\nu>0$, $\delta>0$) Inverse Gamma ($\nu>0$, $\delta>0$) Inverse Gaussian ($\mu>0$, $\lambda>0$)

[9] As years go by, it is likely that the 1987 datum will be filled in and the zero will disappear as the 1987 CPI becomes smaller relative to the current year with the passage of time; in this sense the data set is truncated. Note that average costs do not exist for 1987 but would come into being when the datum gets filled in.

[10] Just what you would think: real total \$billion+ costs, divided by the number of \$billion+ events, year by year. This works because NOAA does not count costs from events that have not cleared the billion-dollar disaster threshold.

LogLogistic (γ>0, σ>0) LogNormal (μ, σ>0) Nakagami (μ>0, ω>0)

Shifted Gompertz (λ>0, ξ) 0-Shifted Gompertz (λ>0, ξ) Weibull (β>0, θ>0).

For most of these distributions, the first parameter is termed a "shape" coefficient, while the second is some measure of distributional width called "scale" or "spread" (or even variance). The exceptions are the Beta Prime, where both are shape parameters; the Gamma, where we use "rate" parameter δ (the reciprocal of the scale parameter, but very much the scale parameter for the Inverse Gamma), owing to its connection to the well-known geometric depreciation rate δ for an asset type whose individual members have Gamma-distributed service-lives; the LogNormal, where the random variable's log-mean is μ and log-variance is σ^2; and the Shifted and 0-Shifted Gompertz, where shape and scale are reversed. Three of the distributions (Beta Prime, LogLogistic, and LogNormal) have thick right tails, whose density functions approach zero at slower-than-exponential rates; eight have thin right tails (i.e., exponential decay); and the Weibull's right tail is thick for β<1 but thin otherwise. With only 42 observations,[11] we do not have the luxury of three- or four-parameter forms for higher moments, leaving these to be settled implicitly by the best nonnested choice among distributions, typically an Akaike-type comparison. In view of all the distributions having the same number of parameters, this boils down to an exponentiated difference among log likelihoods. All 12 of the distributions at least allow a single interior mode, depending on parameter values; half of them (Birnbaum-Saunders, Fréchet, Inverse Gamma, Inverse Gaussian, LogNormal, and 0-Shifted Gompertz) compel it. Alone among the 12, the Shifted Gompertz may increase from a positive density at the origin to an interior mode; one may consider this a feature or a bug. To the extent it is a bug, a

[11] We drop 1987's count and cost of zero here, viewing them as truncation victims, not genuine zeroes.

modification to the 0-Shifted Gompertz form imposes a zero density at the origin.[12] There are surely other two-parameter distributions that we've neglected and could be persuaded to fit, subject to diminishing returns.

These regressions allow for truncation of the billion-dollar minimum in the following way: Any mass below $1 billion is truncated, because unless disasters rise above the billion-dollar threshold their mass cannot appear. So, the regressions select the maximum likelihood distribution for the given density assuming a truncation below $1 billion with 42 positive observations and one truncated.

Rudimentary test-regressions of average real costs against a constant and "latter-part" time-dummy rejected the hypothesis of differences between the earlier and latter parts of the 1980 to 2022 real $billion+ average-cost series *no matter where* the split between early and late was placed. So, the parameters to be estimated for average costs are simple, with the best fit maximizing the log-likelihood implied by a left-truncated Fréchet density:

$$42 \ln \frac{\beta\,\theta^{\beta}}{1 - \mathrm{Exp}[-\theta^{\beta}]} - (1 + \beta) \sum_{t=1980}^{2022} \ln \overline{c_t} - \theta^{\beta} \sum_{t=1980}^{2022} \overline{c_t}^{\,-\beta} \tag{4.1}$$

and the second-best, some 29 percent less likely, maximizing the log-likelihood implied by a left-truncated Inverse Gamma density:

$$42\,(\nu \ln \delta - \ln[\Gamma(\nu) - \Gamma(\nu, \delta)]) - \beta \sum_{t=1980}^{2022} 1/\overline{c_t} - (1 + \nu) \sum_{t=1980}^{2022} \ln \overline{c_t} \tag{4.2}$$

[12] That is, when the other 11 densities have a positive interior mode (i.e., $\sup_x f(x)$ occurs at $x > 0$), they also happen to have $\lim_{x\to 0} f(x) = 0$, while the Shifted Gompertz density still permits $\lim_{x\to 0} f(x) > 0$. The algebraic form of the Shifted Gompertz density is: $f(x) = \lambda\, Exp[-\lambda\, x - \xi\, e^{-\lambda\, x}]\,(1 + \xi(1 - Exp[-\lambda\, x]))$. The modification to the 0-Shifted Gompertz density is: $f(x) = \{\lambda\,(1 + \xi)^2/(\xi + \mathrm{Exp}[-1-\xi])\}\; Exp[-\lambda\, x - (1 + \xi)\, e^{-\lambda\, x}]\,(1 - Exp[-\lambda\, x])$.

Full details of the fits, for these distributions and the other ten, are given in Appendix Table 1.[13]

Both the Fréchet and Inverse Gamma densities are characterized by thin right tails. Appendix Figure 1 provides a visual comparison of the two best estimates against a histogram of real average costs, which shows excellent fits, although it is clear the log-likelihood criterion is rewarding agreement with the mode, not the right tail. The largest outlier, at $51.4 billion, represents a three-month drought in 1988; the next largest, at $41.25 billion, averages across six disasters in 2005, including a six-month drought and four hurricanes. These aren't enough to allay Weitzman's concerns, which use Bayesian updating to infer the cost responses to average temperatures beyond the historical range and could finish with a thick-tailed distribution even from thin-tailed priors; but finding a thick-tailed distribution of average costs now (such as the Beta Prime or LogLogistic, the third and fourth likeliest densities for these data) would have gone some distance to confirm them. Finally, neither the Inverse Gamma nor the Fréchet fits leaves much mass below the $1 billion mark: just two-tenths of a percent of the full Inverse Gamma density, and two *hundredths* of a percent of the full Fréchet. NOAA's billion-dollar cut, then, is harmless from this perspective.

This statistical background to the data then provides us with a new approach to trend growth in total annual costs, if we swap out the simple parameters of the average-cost models for compound parameters permitting constant growth-rates (e.g., $\beta \rightarrow \beta_o \, \mathrm{Exp}[\beta_1(t - 2001)]$). This forces any sign restrictions onto the "β_o"-coefficients, while allowing the time coefficients to go either way. It also compels 42 observations to bear the statistical weight of four unknowns, which not all dozen forms can accommodate. In Appendix Table 2, at least one time coefficient

[13] All the time series in Tables 3 and 8 exclude 1987, so "t = 1980 . . . 2022" really means t = 1980 . . . 1986, 1988 . . . 2022.

is not statistically different from zero for 11 of the 12 distributions (indicated by grayed numbers). Two thin-tailed distributions, the Birnbaum-Saunders and Inverse Gaussian, are about equally likely and at least 63 percent *more* likely than the thick-tailed LogNormal, which finishes third. Of these, we choose the Inverse Normal for closer examination, as all four of its coefficients are significant and its (untruncated) mean is easy to read: $\mu_o \text{Exp}[\mu_1(t\text{–}2001)]$. The μ_1 term is a complementary estimate of the disaster-induced depreciation rate, whose value, $.055 \pm .026$, is essentially the same as the Poisson pseudo-maximum-likelihood regression result but accounts for disasters below the $1 billion cutoff. Over the whole 1980 to 2022 period, the estimated left-truncated conditional mean:

$$\mu_0 \,\text{Exp}[\mu_1 (t - 2001)] \left(\frac{2}{\dfrac{\text{Exp}\left[2 \frac{\lambda_0}{\mu_0} \text{Exp}[(\lambda_1 - \mu_1)(t-2001)]\right] \text{Erfc}\left[\sqrt{\frac{\lambda_0 \text{Exp}[\lambda_1 (t-2001)]}{2 k_t}} \left(1 + \frac{k_t}{\mu_0 \text{Exp}[\mu_1 (t-2001)]}\right)\right]}{\text{Erfc}\left[\sqrt{\frac{\lambda_0 \text{Exp}[\lambda_1 (t-2001)]}{2 k_t}} \left(1 - \frac{k_t}{\mu_0 \text{Exp}[\mu_1 (t-2001)]}\right)\right] - 2} + 1} - 1 \right) \tag{6.3}$$

averages $138 million less than the (left-truncated) observations—essentially unbiased, within the spread of the data. Root mean squared error of $60.4 billion is in line with other distributions.

Appendix Figure 2 plots the trending untruncated mean and its 90 percent confidence interval, as well as the left-truncated conditional mean, against the data used to fit them, making plain the problem: real GDP growth over the same period averaged 2.6 log-points a year, not

[14] The left-truncated mean at (6.3) is conditional on k_t, the count of disasters in year t. We have not estimated the best discrete trending distribution of the counts, which would enable forming an *expected* left-truncated mean as the product of (6.3) and the disaster counts' probability mass function, summed together from zero disasters up.

As it stands, (6.3) already has a lot to unpack. $\mu_o \text{Exp}[\mu_1(t-2001)]$, *outside* the big parentheses, is the untruncated mean. The expression *inside* limits to 1 as k_t drops from 1 to 0 but has been driven near 1 even in years with several disasters, owing to strong trends in the best-fit Inverse Gaussian model. (The parenthetical term in (6.3) averaged 1.11 through 2001 but just 1.01 since then.) The expression includes $\lambda_o \text{Exp}[\lambda_1(t-2001)]$, the time-trending scale term for the Inverse Gaussian distribution. "Erfc" is the complementary error function.

quite half the 5.5 log-point growth rate of the disaster density's simple mean. And we are only counting monetized disasters, not costs that have been kept off the books. Monetized growth at historical rates will not solve this. The data's two apparent outliers—$253.5 billion in 2005, and $373.2 billion in 2017—aren't so extreme. The 2005 disaster cost-sum cleared 98.6 percent of its distribution; the 2017 sum of 18 disasters, including Hurricanes Harvey and Maria that together cost $260.15 billion, exceeded 97.8 percent of its distribution. Appendix Figure 3, showing this time of changes in the Inverse Gaussian density across the start, middle, and end years of the data, suggests thick-tailed damage distributions are less to worry about than the rapid rightward movement of the best-fit thin-tailed ones. The fact that the distribution of the average does not evolve over time does not contradict the possibility that climate events are worsening over time. Since the number of events is rising, with this distribution we see that larger damage events become more likely.

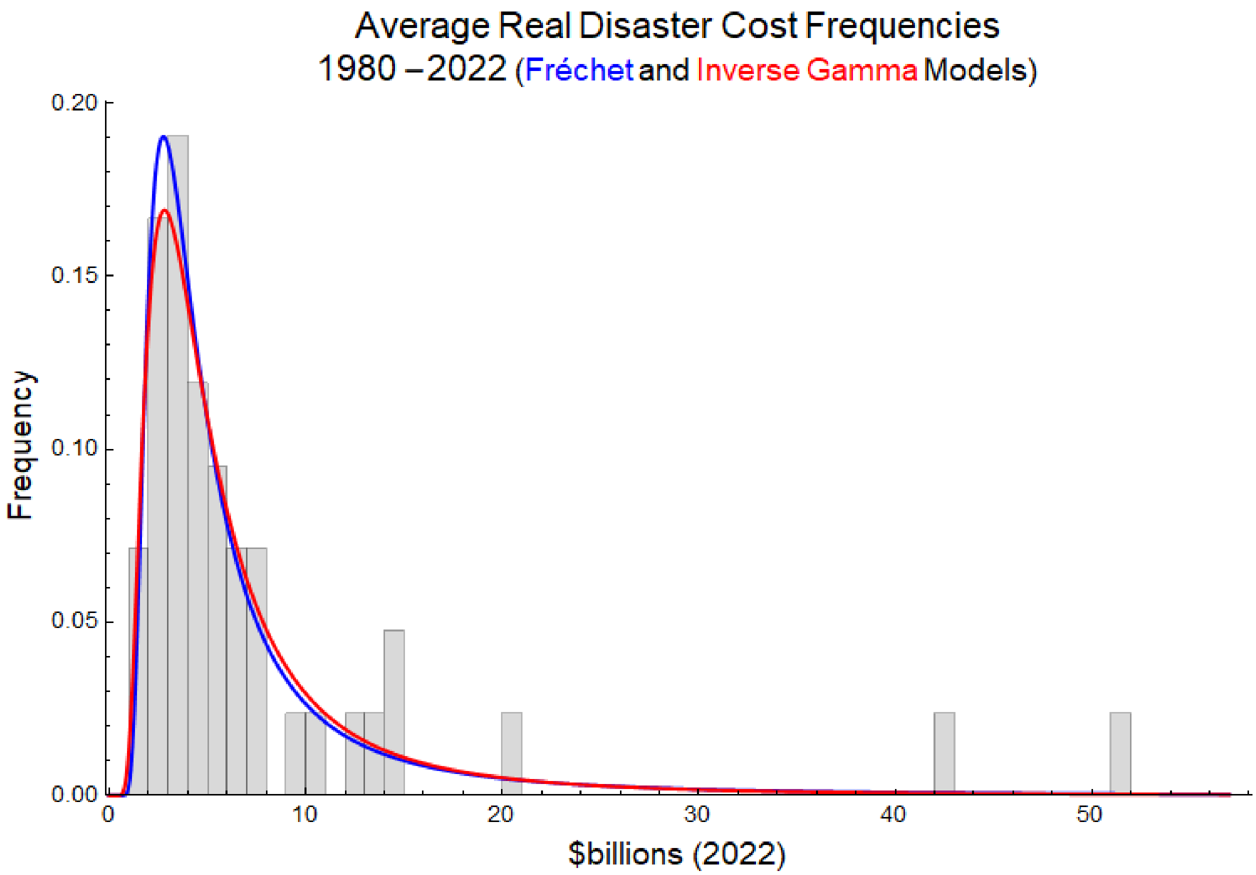
Appendix Table 1: Distributional Fits of Real $Billion+ Disaster Average Costs: All Categories

Right-Skewed Distributions	Log-Likelihood	Relative Likelihood	Estimated Parameters *plus* common names, "symbolic names," and (standard errors)			
Beta Prime	–116.336	.426	shape1: "*p*"	**10.8918** (2.71925)	shape2: "*q*"	**2.479** (.542588)
Birnbaum-Saunders	–119.57	.017	shape: "α"	**.906201** (.118233)	scale: "λ"	**.182144** (.025891)
Fréchet	**–115.482**	**1.000**	shape: "β"	**1.6282** (.198986)	scale: "θ"	**3.68885** (.368901)
Gamma	–121.937	.002	shape: "ν"	.679122 (.364234)	rate: "δ"	**.113359** (.0430756)
Inverse Gamma	**–115.828**	**.708**	shape: "ν"	**2.17369** (.455594)	scale: "δ"	**8.90382** (2.14577)
Inverse Gaussian	–118.128	.071	mean: "μ"	**7.68018** (1.16037)	scale: "λ"	**8.03213** (2.11652)
LogLogistic	–117.047	.209	shape: "γ"	**2.15336** (.332659)	scale: "σ"	**4.68154** (.601382)
LogNormal	–118.153	.069	log mean: "μ"	**1.60533** (.14495)	log st.dev.: "σ"	**.839389** (.114362)
Nakagami	–124.612	.000	shape: "μ"	.0176309 (.103573)	spread: "ω"	16.1309 (89.1938)
Shifted Gompertz	–120.288	.008	scale: "λ"	**.08393** (.0226204)	shape: "ξ"	**–.820207** (.186773)
0-Shifted Gompertz	–118.386	.055	scale: "λ"	**.0691993** (.0272583)	shape: "ξ"	**–6.97187** (2.07595)
Weibull	–121.325	.003	shape: "β"	**.79129** (.15161	scale:	**5.22268**

<u>Appendix Table 2. Distributional Fits of Real $Billion+ Disaster Total Costs: All Categories</u>

Right-Skewed Distributions	**Log-Likelihood**	**Relative Likelihood**	**Bias ($b)**	**RMSE ($b)**	**Estimated Compound Parameters** *plus* common names, "symbolic names," and (standard errors)			
Beta Prime	–197.673	.485	8.901	61.241	shape1:	**40.5052** *Exp*[**.0811699** (*t*–2001)]	shape2:	**1.75943** *Exp*[.0168785 (*t*–2001)]
					"*p*"	(11.7806) (.0235713)	"*q*"	(.376558) (.0167904)
Birnbaum-Saunders	**–196.950**	**1.000**	0.085	60.309	shape:	**.980061** *Exp*[–.0136655 (*t*–2001)]	scale:	**.0335939** *Exp*[–.**0645278** (*t*–2001)]
					"α"	(.149781) (.0122796)	"λ"	(.00685833) (.0161629)
Fréchet	–197.849	.407	26.656	66.549	shape:	**1.37813** *Exp*[.0110488 (*t*–2001)]	scale:	**20.7513** *Exp*[**.0634793** (*t*–2001)]
					"β"	(.182445) (.0101076)	"θ"	(3.00922) (.0119986)
Gamma	–198.203	.286	–.089	59.986	shape:	**.784585** *Exp*[.0349533 (*t*–2001)]	rate:	**.0213649** *Exp*[–.0289422 (*t*–2001)]
					"ν"	(.433373) (.0456968)	"δ"	(.00776772) (.0301939)
Inverse Gamma	–197.704	.470	11.190	61.827	shape:	**1.70236** *Exp*[.0186451 (*t*–2001)]	scale:	**38.1375** *Exp*[**.084663** (*t*–2001)]
					"ν"	(.360215) (.0165422)	"δ"	(11.002) (.023096)
Inverse Gaussian	**–196.987**	**.964**	–.138	60.388	mean:	**45.1276** *Exp*[**.0549304** (*t*–2001)]	scale:	**40.8526** *Exp*[**.0815162** (*t*–2001)]
					"μ"	(7.62016) (.0130145)	"λ"	(12.682) (.0254605)
LogLogistic	–198.356	.245	7.940	60.902	shape:	**1.75545** *Exp*[**.0152873** (*t*–2001)]	scale:	**27.0669** *Exp*[**.065988** (*t*–2001)]
					"γ"	(.27844) (.0127781)	"σ"	(5.64875) (.0167152)
LogNormal	–197.476	.591	**–.002**	60.228	log mean:	**3.27848** *Exp*[**.0184774** (*t*–2001)]	log st.dev.:	**.923171***Exp*[**–.0133995** (*t*–2001)]
					"μ"	(.218002) (.00472766)	"σ"	(.133325) (.0112629)
Nakagami	–198.969	.133	2.045	**59.717**	shape:	**.133338** *Exp*[**.0416551** (*t*–2001)]	spread:	**2066.40** *Exp*[**.130442** (*t*–2001)]
					"μ"	(.168947) (.105312)	"ω"	(2088.39) (.0784113)
Shifted Gompertz	–198.435	.227	.233	59.860	scale:	**.0201948** *Exp*[**–.0517307** (*t*–2001)]	shape:	–.369074 *Exp*[–.00177979 (*t*–2001)]
					"λ"	(.0093601) (.0226891)	"ξ"	(.652717) (.0759158)
0-Shifted Gompertz	–198.333	.251	–.925	60.141	scale:	**.0171497** *Exp*[–.0634646 (*t*–2001)]	shape:	**–4.71906** *Exp*[.00892219 (*t*–2001)]
					"λ"	(.0112181) (.0422827)	"ξ"	(2.77569) (.0355841)
Weibull	–198.329	.252	–.206	59.927	shape:	**.892922** *Exp*[.0109593 (*t*–2001)]	scale:	**36.0153** *Exp*[**.0631081** (*t*–2001)]
					"β"	(.181389) (.0169996)	"θ"	(10.7001) (.02398)

Appendix Figure 1.



Notes:

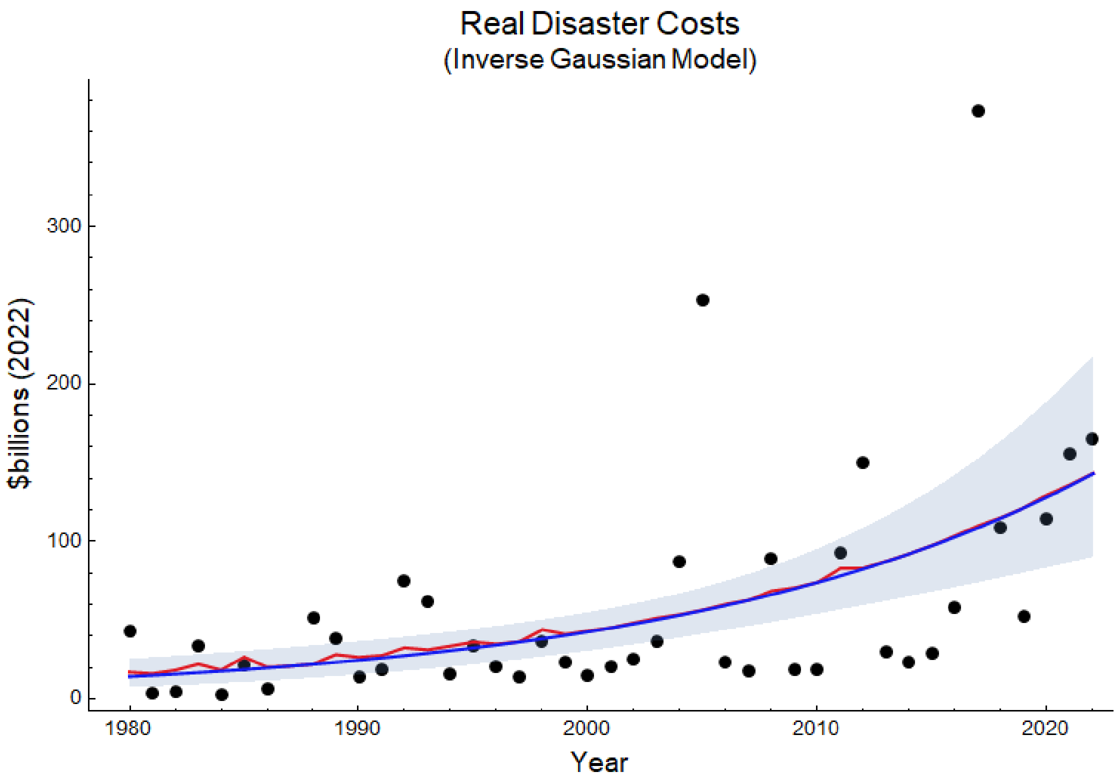
`Shaded Bars = histogram of $1b+ disasters`

Blue Line = Fréchet probability density function (100% of disasters ≥ $0)

Red Line = Inverse Gamma probability density function (100% of disasters ≥ $0)

Costs are deflated by the 2022 CPI.

Appendix Figure 2.



Notes:

Rough Red Line = fitted left-truncated means (used in calculations of bias and RMSE)

Smooth Blue Line = estimated complete means (used for the time-based damage function)

Shaded Region = 90% confidence interval about complete means

Costs are deflated by the 2022 CPI.

Appendix Figure 3.