The Increasing Pace of Weather-Related Cost Shocks: Should Net Domestic Product be Affected by Climate Disasters?

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Abstract The monetary costs of weather and climate disasters in the United States grew rapidly from 1980 to 2022, rising more than 5 percent in real terms annually, and implying a faster depreciation of real assets. We argue that the expected depreciation from these events could be included in consumption of fixed capital, leading to lower levels, and slightly slower growth rates, of net domestic product. We use Poisson pseudo-maximum-likelihood regressions to estimate this expectation and generate our experimental measure of costs. An alternative calculation of depreciation and net domestic product might be derived from the time series of costs incurred, rather than the far smoother expectation. This latter, realized series might be more appropriate for a national income satellite account. We also investigate the parametric distributions of annual average and total disaster-cost data.

Keywords Depreciation, national accounts, weather disasters

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1. Introduction

The number and total yearly costs of weather-related disasters has increased markedly over the past 40 years, to the extent that disasters associated with the changing climate may be considered, from a macroeconomic perspective, as much features of an expectational process as shocks. This has implications for national accounting. In this paper, we focus on the inadvertent exclusion of the costs of U.S. weather and climate disasters from existing measures of asset depreciation. We show such costs represent an appreciable and growing proportion of depreciation, we consider two ways to treat them, and we embed them in a statistical process which is amenable to forecasting.

Net domestic product (NDP) does not as currently measured take into account catastrophic losses. As a result, NDP may correlate less well with well-being than it could. (Net domestic product as such is not a measure of well-being; improving its relationship with well-being is useful to the extent NDP growth is taken as a desideratum of economic policy. *Cf.* Weitzman 1976.)[1] Currently, an asset-destroying climate event does not appear as a reduction in net domestic product, although it reduces well-being and capital assets. If a destroyed structure is replaced by new construction, the construction appears as a positive investment; the destruction appears in other changes in the volume of assets (OCVA), so the asset volume remains accurate. But NDP will fail to reflect the costs of the event.

We propose two alternative methods by which some climate and weather shocks might appear in NDP or expanded NDP (Hulten and Nakamura 2022), using the U.S. National Oceanic and Atmospheric Administration's (NOAA's) time series of billion dollar weather and climate Disasters (BWCD). Method one is to incorporate the smoothed time series as an expected cost in consumption of fixed capital (CFC), that is, in depreciation, and have the residuals appear in OCVA. Method two is to incorporate the unsmoothed time series costs in CFC, which introduces substantial shocks to NDP and might be better put in a satellite account.

NOAA has constructed the BWCD time series in the United States from 1980 to the present. It estimates the cost of disaster events amounting to $1 billion in economic losses or more, where these are measured in real dollars of the most recent year (here 2022), 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

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1. Hulten and Nakamura (2022) argue that under the Beyond GDP project (Landefeld et al. 2020), it is desirable to have an expanded version of gross domestic product (GDP) that extends its measurement to include changes in consumption technology that is costless. Losses such as climate disasters might be included in this expanded version or might be included directly in net domestic product. The latter possibility is discussed here.

types: flood, drought, freeze, wildfire, and three types of storms (winter, tropical cyclone, and severe). This time series is built upon governmental estimates and private insurance costs, 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 business interruption and housing services, which should be removed, although we do not do so here. In the decade from 2013 to 2023, the average annual U.S. BWCD cost was $111 billion, or 0.5 percent of gross domestic product (GDP).

In this paper, we discuss the 43-year time series of climate shocks from 1980 to 2022 in NOAA's BWCD data set. The simple analysis we perform suggests that weather-related costs have a large variance and are growing at a real rate of roughly 5.5 percent annually, appearing to double every 13 years. This rate of increase is substantially faster than GDP growth, and its capture in and allocation among the national accounts are not straightforward. Broader measures connecting the macroeconomy to the environment within which it operates, such as the social cost of carbon or the value of natural capital, might indicate still greater cost levels and growth rates or undervalued resources, but they face knotty accounting issues such as the proper treatment of unignorable externalities and are in any event excluded from NOAA's careful enumeration of climate and weather disasters, on which we focus.

2. Existing Literature

This paper explores how to include the economic costs of weather and climate disasters in the national accounts. It does so by building upon the work of Reinsdorf *et al.* (2017), who propose a method for incorporating expected financial losses in the national accounts. There is a literature on trends in disaster costs, including work on insurance costs (Swiss Re Institute 2022) and on U.S. weather and climate disasters (Smith and Katz, 2015, and Shukla 2019). 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 4. 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.

3. The Data From NOAA

NOAA's National Centers for Environmental Information collects data on billion-dollar weather and climate disaster. From the NOAA website:

> 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.

Briefly, much of the data are drawn from Federal Emergency Management Agency (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, as these are deducted from other parts of NDP, e.g., residential services.

The second column in table 1 shows the number of BWCD 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 2022. As time passes, more past events qualify as billion-dollar disasters, since the CPI has risen over time and so the value of a billion dollars becomes smaller relative to the past. In 1980, for example, originally there was only one disaster, a $10 billion cost drought and heatwave in the summer and fall, that passed the billion-dollar mark. Now, measured in 2022 dollars, there are three events that qualify, and the drought/heatwave event is reckoned at $38 billion. In the decade from 1980 to 1989, NOAA recorded an average of 3.1 events that cost a billion dollars or more, using the prices of 2022. By comparison, from 2013 to 2022, there were 15.1 such events a year.

The third column in table 1 shows the aggregate time series of BWCD costs from NOAA covering the period from 1980 to 2022, as published in February 2023. In summary, in the decade from 1980 to 1989, total annual BWCD costs averaged $20.5 billion, while in the decade from 2013 to 2022, they averaged $111 billion, for a real compound annual growth rate of 5.3 percent. Figure 1 depicts graphically that in the period from 1980 to 2000, there are no years with shock costs greater than $100 billion, while there are five from 2001 to 2022. The fourth column in table 1 gives the centered 10-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 2. Figure 1 shows the time series of annual costs together with the centered moving average.

4. Statistical Description of Annual Data

The regression work of the paper in section 5, below, contrasts the usual log-linear approach to estimation, which faces problems when the dependent variable is zero (e.g., as in 1987, when no disasters cleared the billion-dollar threshold) and which can be biased downward in the levels,[2] with the consistent but heteroskedastic Poisson pseudo-maximum-likelihood estimator.[3] The annual data may also be treated in a more thoroughgoing statistical manner, in the hope of approaching the distributions that best describe the real *average* annual $billion+ disaster-cost[4] and *total* $billion+ disaster-cost series. The statistical approach also 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 $1 billion each), and so can answer the question of how much sub-$billion disasters matter. Finally, the choice of distribution might bear on Weitzman's apprehensions of thick-tailed climate risks.

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2. 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 nonparametric smearing transformation (1983) would apply beyond the lognormal case and has been used by health econometricians.

3. See Gourieroux, Monfort, and Trognon (1984) for the original work, and Santos Silva and Tenreyro (2006), who implement the PPML in a trade setting after considering some related alternatives.

4. Just what you'd think: real total $billion + costs, divided by the number of $billion + events, year by year. This works because NOAA doesn't count costs from events that haven't cleared the $billion disaster threshold.

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 (α>0, λ>0)	Fréchet (β>0, θ>0)
Gamma (ν>0, δ>0)	Inverse Gamma (ν>0, δ>0)	Inverse Gaussian (μ>0, λ>0)
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 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 (e.g., the 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); the Weibull's right tail is thick for β<1 but thin otherwise. With only 42 observations,[5] we do not have the luxury of three- or four-parameter forms for higher moments, leaving these to the 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 (i.e., the Birnbaum-Saunders, Fréchet, Inverse Gamma, Inverse Gaussian, LogNormal, and 0-Shifted Gompertz) compel it. Alone among the twelve, 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 modification to the "Zero-Shifted Gompertz" form imposes a zero density at the origin.[6] There are surely other two-parameter distributions that we've neglected and could be persuaded to fit, subject to diminishing returns.

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5. We drop 1987's count and cost of "0" here, viewing them as truncation victims, not genuine zeroes.

6. 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: $f(x) = \lambda\ \mathrm{Exp}[-\lambda x - \xi e^{-\lambda x}]\ (1 + \xi(1 - \mathrm{Exp}[-\lambda x]))$. The modification to the "Zero-Shifted" Gompertz density is: $f(x) = \{\lambda (1 + \xi)^2/(\xi + \mathrm{Exp}[-1-\xi])\}\ \mathrm{Exp}[-\lambda x - (1 + \xi) e^{-\lambda x}]\ (1 - \mathrm{Exp}[-\lambda x])$.

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 1980–2022 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:

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

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

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

Full details of the fits, for these distributions and the other ten, are given in table 3, below.[7]

Both the Fréchet and Inverse Gamma densities are characterized by thin right tails. A visual comparison of the two best estimates against a histogram of real average costs (figure 2, below) shows excellent fits, though 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 6-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 would 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 fit 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, sacrifices almost no information.

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7. In (4.1), (4.2), and table 3, $\overline{c_t}$ represents average deflated costs (in $billions) in year t. In table 6, ct represents total deflated costs (in $billions) in year t. In all the time-series in tables 3 and 6 exclude 1987, so the index "t = 1980...2022" really means t = 1980...1986, 1988...2022.

5. National Accounts Methodology

National production accounts are calculated on both a gross and a net basis, the difference between the two being consumption of fixed capital. The question we address here is to what extent consumption of fixed capital should include the expected cost of weather and climate disasters.

Weather and climate disasters, according to SNA 2008, are included in "other changes in the volume of assets," chapter 12. Basically, other changes in volume of assets are changes to capital assets that do not flow normally from economic activity. From page 208:

> §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.

These disasters are not included in consumption of fixed capital, unless they are included in accidental normal damage. From page 123, chapter 6 (the production account):

> §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.

NDP is a measure of output, and catastrophic losses are not per se direct sources of changes in output (although they may have large impacts on output by, for example, temporarily disrupting workplaces). But it appears that weather and climate disasters are systematically increasing in number and cost due to climate change. If so, perhaps the expected component of these costs should be included in the consumption of fixed capital.

Methodologically, this paper relies upon Reinsdorf *et al.* (2017), which discusses how to include expected losses in finance to improve System of National Accounting methods. For example, credit card interest payments to financial intermediaries overstate the expected interest from credit card debt, as expected losses due to defaulting borrowers are high. The consumer services of financial institutions include financial institution services indirectly measured (FISIM), which is, under SNA, 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 is overstated. But 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 Bureau of Economic Analysis' treatment of FISIM to incorporate certain expected losses by financial intermediaries.

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, we calculate the trend in BWCD 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 a smaller growth rate of NDP, although the impact is a small one, as we shall see.

A related consideration here is how we account for non-life insurance activities as part of personal consumption expenditures for insurance. The preferred measure of their value is premiums net of expected losses. What do we mean by expected losses of catastrophes? What is the normal part of such losses that are likely to appear in non-life insurers' calculations of insurance premia? We make the argument in this paper that, with climate change, the expected losses of catastrophes are rising. This in turn affects the net value added component of premiums, and in turn is likely to affect the expected rents to structures and their operators (whether firms or owner-operators). At present, catastrophes are included in costs as spread out over the following 20 years, which will not account for expected rises in catastrophes. See the technical note in chapter 5 of the *National Income and Product Accounts Handbook* for BEA's treatment of catastrophes for non-life insurance in U.S. personal consumption expenditures.

6. Measuring Expected Costs

We now turn to the estimation of the expected component of BWCD to guide an experimental measurement of consumption of fixed capital.

Experimental measurement of consumption of fixed capital

Method one: *expected* catastrophic losses due to climate and weather

Method one uses a log trend to estimate expected BWCD costs and proposes to add these expectations to consumption of fixed capital. To estimate this expectation, we use two types of regressions. The first type is a conventional OLS regression of log BWCD costs on time:

$$\ln(BWCD_t) = a + b\ time + \varepsilon_t \tag{6.1}$$

The second is a Poisson pseudo-maximum-likelihood regression of BWCD costs on an exponential function of time:

$$BWCD_t = \exp(a + b\ time) + \ \varepsilon_t \tag{6.2}$$

OLS regressions of log annual BWCD on time. The first regression of log losses can be used to capture the exponential trend growth, but then there were no billion-dollar disasters in 1987 and the log of zero does not exist, so we need either to add a dummy variable for that date, or to replace the zero with 1, whose log is zero, an approximation often used empirically. The dummy variable will tend to underestimate the growth rate (because it in effect replaces an unusually small number with an average value), and so is the more conservative choice. The output of the regression with a 1 inserted for 1987's costs (so that the log is zero) is presented in table 4, column 1: .0591, which translates to a trend growth rate of 6.09 percent per year. The output of the regression with a dummy variable included for 1987 is shown in column 2: .0533, for a trend growth rate of 5.47 percent per year.

One difficulty of using the log trendline as expected loss is that NDP is an additive measure. Under these circumstances where the loss is rising, the log trendline will tend to undermeasure the average loss. Taking logs takes arithmetically large positive errors and reduces them relative to negative errors. This issue is discussed in Santos Silva and Tenreyro (2006), who argue, in the context of the gravity equation for trade, that by Jensen's inequality — here $E(\ln y) \leq \ln E(y)$ — the usual log-linear regression in the presence of heteroscedasticity is not just inefficient but biased. They suggest using Poisson pseudo-maximum-likelihood estimation techniques instead.

In table 1, the fifth column shows the expected costs from the dummy regression. The values are persistently below the 10-year moving averages in the fourth column, which we would expect given the Santos Silva and Tenreyro argument.[8]

Poisson pseudo-ML (PPML) regression of annual BWCD on exponential of time. The first advantage of using PPML rather than log-linear regression for these 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 cost growth of BWCD, output shown in table 4 column 3. The coefficient .0546 translates to a trend growth rate of 5.61 percent per year, between those of the two previous regressions.

Figure 3 depicts our preferred measure of expected cost in comparison to actual costs. Figure 4 shows our preferred measure together with the conservative measure from the log regression specification and the ten-year moving average of costs. Note that generally speaking, our preferred measure traces the moving average much more closely than the conservative log trend. The coefficient standard errors of the two regressions are close to one another; we interpret this as a modest win for our preferred measure, since the conservative measure has a dummy that reduces the residual in 1987 to zero.

Further exploration of the methodology is warranted. 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.

To compare the impact of the trend on CFC and NDP, table 5 provides useful information in nominal terms. We use nominals because of the inaccuracy that would be introduced by, for example, using the CFC deflator to deflate BWCD costs. Nominal BWCD costs and the trend measure are constructed by reflating the real data using the CPI-U after setting the CPI-U to a 2022 base of 100.

If we view the trendline as the expected loss, then these expected losses have risen from 0.17 percent of NDP to 0.70 percent. If we were to subtract these from NDP, the effect for the 42 years would be to decrease the annual growth rate of NDP by 0.013 percentage points, in nominal terms from 5.156 to 5.143 percent (note that with the magic of rounding, this is a change from 5.2 percent to 5.1 percent).

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8. Also, see note 4, above.

The impact on the overall rate of depreciation is more noticeable. Without including BWCD, 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 BWCD, CFC as a proportion of NDP is 17.8 percent in 1980 and 20.9 percent in 2022.

We can further pursue trend growth in total annual costs using the techniques of section 4, if we swap out the simple parameters of the *average*-cost models for *total*-cost models with 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 4 unknowns, which not all dozen forms can accommodate. In table 6, at least one time coefficient 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: $\mu_o \,\mathrm{Exp}[\mu_1(t\text{–}2001)]$. 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 PPML regression result but accounts for disasters below the \$1 billion cutoff. Over the whole 1980–2022 period, the estimated left-truncated conditional mean…

$$\mu_0 \,\mathrm{Exp}[\mu_1 (t-2001)] \left(\frac{2}{\dfrac{\mathrm{Exp}\left[2 \frac{\lambda_0}{\mu_0} \mathrm{Exp}[(\lambda_1-\mu_1)(t-2001)]\right] \mathrm{Erfc}\left[\sqrt{\frac{\lambda_0 \,\mathrm{Exp}[\lambda_1 (t-2001)]}{2 k_t}} \left(1+\frac{k_t}{\mu_0 \,\mathrm{Exp}[\mu_1 (t-2001)]}\right)\right]}{\mathrm{Erfc}\left[\sqrt{\frac{\lambda_0 \,\mathrm{Exp}[\lambda_1 (t-2001)]}{2 k_t}} \left(1-\frac{k_t}{\mu_0 \,\mathrm{Exp}[\mu_1 (t-2001)]}\right)\right]-2}+1} - 1 \right) \ldots^{9} \qquad (6.3)$$

…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.

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9. The left-truncated mean at (6.3) is conditional on kt, 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. μo Exp[μ1(t–2001)], outside the big parentheses, is the untruncated mean. The expression inside limits to 1 as kt 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 λo Exp[λ1(t–2001)], the time-trending scale term for the Inverse Gaussian distribution. "Erfc" is the complementary error function.

Figure 5 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 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, which together cost $260.15 billion, exceeded 97.8 percent of its. In figure 6, 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.

Further exploration of NOAA's $billion+ disaster data might include disaggregating the average-cost and total-cost work to the seven disaster-type categories that comprise them, experimenting with different deflators than the CPI, in view of the likely greater monetary losses incurred to structures than their weight in the CPI, and replacing time as the trend-driver with some measure(s) of the temperature anomaly, which in principle ought to be more governable than time.[10]

Method two: realized catastrophic losses due to climate and weather

GDP and NDP are *ex post* measures. Using expectations and smoothing trendlines is not necessarily the best way of capturing outcomes. In this spirit, one could subtract the unsmoothed losses of BWCD from NDP. This better captures the welfare impact of weather and climate 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 with its relationship to other economic variables, such as employment. 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.

Table 5 column 6 shows BWCD as a percentage of annual NDP. It can be seen that these have a visible impact on NDP. In 2017, the combined impacts of Hurricanes Harvey, Irma, and Maria—three of the five most expensive hurricanes in the time series, the others being Hurricane Katrina (2005) and Superstorm Sandy (2012)—caused $265 billion in damage out of a total of $313 BWCD costs. 2017 BWCD was 1.9 percent of NDP, following on 0.3 percent of NDP in the previous year. The difference of 1.6 percentage points would likely have reduced real NDP 2017 growth from 2.15 percent to 0.5 percent. This very slow growth rate may have better reflected the change in well-being in that year of dreadful storms and fires than the original or than method one. The counterpart would have been a much higher growth rate from 2017 to 2018.

[10] All quantitative work behind tables 3 and 6 and figures 2, 5, and 6 was performed with *Mathematica* version 12.

7. Summary

In brief, in this paper we outline two experimental methods for adjusting consumption of fixed capital for catastrophic climate losses to make more visible the rising impact of these losses in NDP. Method one has a very small impact on the growth rate of NDP but reduces NDP's level by 0.4 percent, while method two can have substantial impacts on the year-to-year growth of NDP. This reflects only one source of weather-related effects. The underlying data need some further work to remove some climate and disaster costs that are not destruction of assets; and the disaggregation of these high-level results by asset type and by region would enable more fruitful integration into the national accounts.

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Table 1. Annual U.S. Billion-Dollar Disasters
[CPI-Adjusted to 2022 $ billion]

(1) Year	(2) Number of disasters	(3) All disasters cost	(4) 10-year moving average of disaster cost	(5) Trendline from regression 1 (delogged)	(6) Trendline from regression 2
1980	3	43.1		11.0	14.7
1981	2	3.3		11.6	15.5
1982	3	5.1		12.2	16.4
1983	5	33.3		12.9	17.3
1984	2	3	20.5	13.6	18.3
1985	7	21.4	17.6	14.3	19.3
1986	2	6.3	19.1	15.1	20.4
1987	0	0	26.1	15.9	21.6
1988	1	51.4	29.0	16.8	22.8
1989	6	38	30.3	17.7	24.1
1990	4	13.8	31.5	18.7	25.5
1991	4	18.5	32.9	19.7	26.9
1992	7	75.4	34.4	20.8	28.4
1993	5	62	32.9	21.9	30.0
1994	6	15.7	31.4	23.1	31.7
1995	7	33.7	31.4	24.4	33.5
1996	4	20.7	31.6	25.7	35.4
1997	3	14.3	26.7	27.1	37.4
1998	10	36.4	24.1	28.6	39.5
1999	5	23.1	31.3	30.2	41.7
2000	5	14.6	53.2	31.8	44.1
2001	3	20.5	53.5	33.5	46.6
2002	6	25.7	53.9	35.4	49.2
2003	7	36.3	59.1	37.3	52.0
2004	6	87.2	58.7	39.4	54.9
2005	6	253.5	59.1	41.5	58.0
2006	8	23.8	66.3	43.8	61.3
2007	5	17.8	78.8	46.2	64.8
2008	12	88.8	78.2	48.7	68.4
2009	9	18.6	71.8	51.4	72.3
2010	7	18.9	49.4	54.2	76.4
2011	18	92.4	52.7	57.1	80.7
2012	11	150.3	88.3	60.3	85.3
2013	10	30.4	90.3	63.6	90.1
2014	9	23.1	93.6	67.1	95.2
2015	11	29.4	103.2	70.7	100.6
2016	15	57.7	109.5	74.6	106.2
2017	18	373.2	110.9	78.7	112.2
2018	15	108.5		83.0	118.6
2019	14	52.4		87.5	125.3
2020	22	114.3		92.3	132.4
2021	20	155.3		97.4	139.8
2022	18	165		102.7	147.7

U.S. National Oceanic and Atmospheric Administration, Billion Dollar Weather and Climate Disasters, 2022

Table 2. Decade Averages of U.S Billion-Dollar Climate and Weather Disaster Events and Costs
[2022 dollars (based on CPI)]

Decade	Number of billion-dollar disasters	Cost of billion-dollar disasters, billions of dollars	Cost per disaster, Billions of dollars
1980–89	3.1	20.5	6.6
1990–99	5.5	31.4	5.7
2000–09	6.7	58.7	8.8
2010–19	12.8	93.6	7.3
2013–22	15.2	110.9	7.3

Table 3: 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** (.151618)	scale: "θ"	**5.22268** (1.62971)

Table 4. Coefficients on Time in Trend Regressions

	(1)	(2)	(3)
Time	.0591	.0533	.0546
st. err.	.0168	.0161	.0107
(prob)	(.000)	(.000)	(.000)
Dummy for 1987	No	Yes	No
1987 cost =1	Yes	Yes	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. Standard errors are robust. Results for non-robust and for bootstrap standard errors are similar and available upon request.

Table 5. 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				
(1) Year	(2) NDP	(3) CFC	(4) BWCD Costs	(5) Trend	(6) BWCD costs	(7) trend	(8) CFC	(9) CFC+ costs	(10) CFC + Trend
1980	2428.9	428.4	12.1	4.1	0.50%	0.17%	17.6%	18.1%	17.8%
1981	2719.8	487.2	1.0	4.8	0.04%	0.18%	17.9%	18.0%	18.1%
1982	2806.8	537.0	1.7	5.4	0.06%	0.19%	19.1%	19.2%	19.3%
1983	3071.4	562.6	11.3	5.9	0.37%	0.19%	18.3%	18.7%	18.5%
1984	3439.2	598.4	1.1	6.5	0.03%	0.19%	17.4%	17.4%	17.6%
1985	3698.9	640.1	7.9	7.1	0.21%	0.19%	17.3%	17.5%	17.5%
1986	3894.3	685.3	2.4	7.7	0.06%	0.20%	17.6%	17.7%	17.8%
1987	4124.8	730.4	0.0	8.4	0.00%	0.20%	17.7%	17.7%	17.9%
1988	4451.9	784.5	20.8	9.2	0.47%	0.21%	17.6%	18.1%	17.8%
1989	4803.3	838.3	16.1	10.2	0.34%	0.21%	17.5%	17.8%	17.7%
1990	5074.6	888.5	6.2	11.4	0.12%	0.22%	17.5%	17.6%	17.7%
1991	5225.7	932.4	8.6	12.5	0.16%	0.24%	17.8%	18.0%	18.1%
1992	5560.1	960.2	36.2	13.6	0.65%	0.25%	17.3%	17.9%	17.5%
1993	5855.1	1003.5	30.6	14.8	0.52%	0.25%	17.1%	17.7%	17.4%
1994	6231.6	1055.6	8.0	16.1	0.13%	0.26%	16.9%	17.1%	17.2%
1995	6517.3	1122.4	17.5	17.4	0.27%	0.27%	17.2%	17.5%	17.5%
1996	6897.8	1175.3	11.1	19.0	0.16%	0.28%	17.0%	17.2%	17.3%
1997	7338.3	1239.3	7.8	20.5	0.11%	0.28%	16.9%	17.0%	17.2%
1998	7753.1	1309.7	20.3	22.0	0.26%	0.28%	16.9%	17.2%	17.2%
1999	8232.3	1398.9	13.2	23.8	0.16%	0.29%	17.0%	17.2%	17.3%
2000	8739.8	1511.2	8.6	25.9	0.10%	0.30%	17.3%	17.4%	17.6%
2001	8982.4	1599.5	12.4	28.2	0.14%	0.31%	17.8%	17.9%	18.1%
2002	9271.1	1658.0	15.8	30.3	0.17%	0.33%	17.9%	18.1%	18.2%
2003	9737.4	1719.1	22.8	32.7	0.23%	0.34%	17.7%	17.9%	18.0%
2004	10395.4	1821.8	56.3	35.5	0.54%	0.34%	17.5%	18.1%	17.9%
2005	11068.2	1971.0	169.2	38.7	1.53%	0.35%	17.8%	19.3%	18.2%
2006	11691.5	2124.1	16.4	42.2	0.14%	0.36%	18.2%	18.3%	18.5%
2007	12221.4	2252.8	12.6	45.9	0.10%	0.38%	18.4%	18.5%	18.8%
2008	12411.1	2358.8	65.3	50.4	0.53%	0.41%	19.0%	19.5%	19.4%
2009	12106.6	2371.5	13.6	53.0	0.11%	0.44%	19.6%	19.7%	20.0%
2010	12658.1	2390.9	14.1	56.9	0.11%	0.45%	18.9%	19.0%	19.3%
2011	13125.2	2474.5	71.0	62.0	0.54%	0.47%	18.9%	19.4%	19.3%
2012	13678	2576.0	117.9	66.9	0.86%	0.49%	18.8%	19.7%	19.3%
2013	14162	2681.2	24.2	71.7	0.17%	0.51%	18.9%	19.1%	19.4%
2014	14735.7	2815.0	18.7	77.0	0.13%	0.52%	19.1%	19.2%	19.6%
2015	15294.6	2911.4	23.8	81.5	0.16%	0.53%	19.0%	19.2%	19.6%
2016	15708	2987.1	47.3	87.1	0.30%	0.55%	19.0%	19.3%	19.6%
2017	16358.6	3118.7	312.6	94.0	1.91%	0.57%	19.1%	21.0%	19.6%
2018	17257.5	3275.6	93.1	101.8	0.54%	0.59%	19.0%	19.5%	19.6%
2019	17944.4	3436.6	45.8	109.5	0.26%	0.61%	19.2%	19.4%	19.8%
2020	17482.7	3577.8	101.1	117.1	0.58%	0.67%	20.5%	21.0%	21.1%
2021	19483.5	3831.6	143.8	129.5	0.74%	0.66%	19.7%	20.4%	20.3%
2022	21177	4284.3	165.0	147.7	0.78%	0.70%	20.2%	21.0%	20.9%
Growth rate 1980–2022	5.2%	5.5%	6.2%	8.5%					

Table 6: DISTRIBUTIONAL FITS OF REAL $BILLION+ DISASTER TOTAL COSTS: ALL CATEGORIES

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

Figure 1. Real Billion Dollar Weather and Climate Disasters and 10-Year Centered Moving Average
(billions of 2022 dollars, deflated by CPI-U)

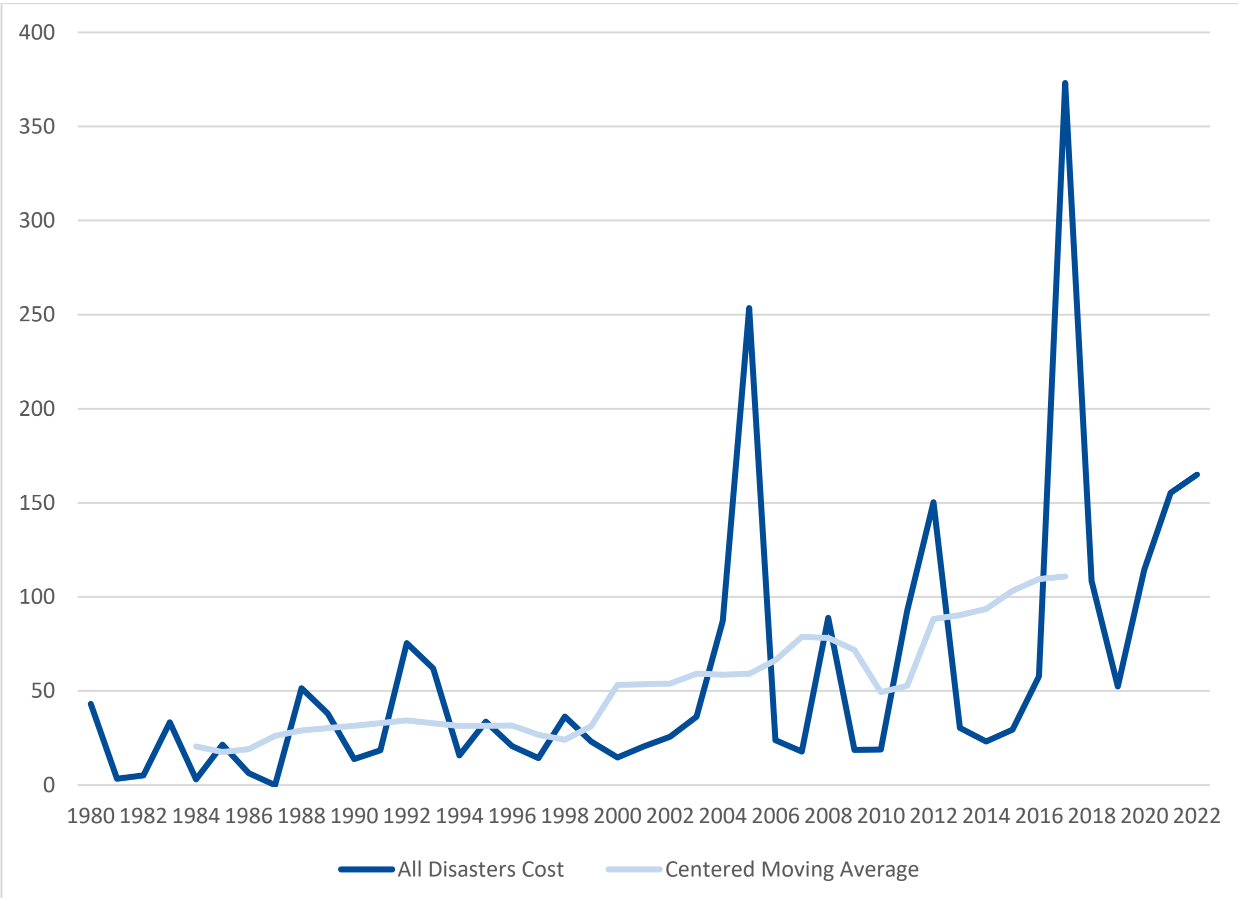
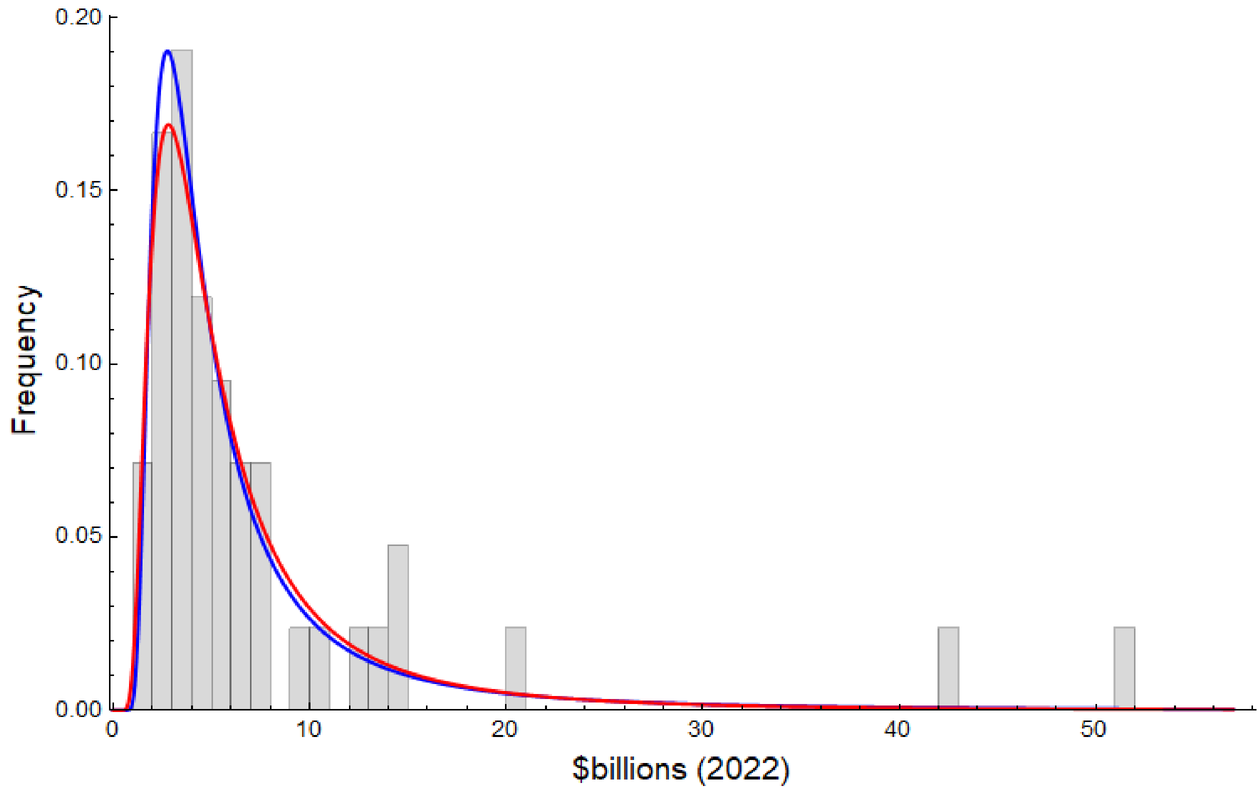


Figure 2. Average Real Disaster Cost Frequencies, 1980–2022
(**Frechet** and **Inverse Gamma** Models)



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 Consumer Price Index.

Figure 3. Annual Disaster Costs and Trends from Exponential Regression and Log Regression

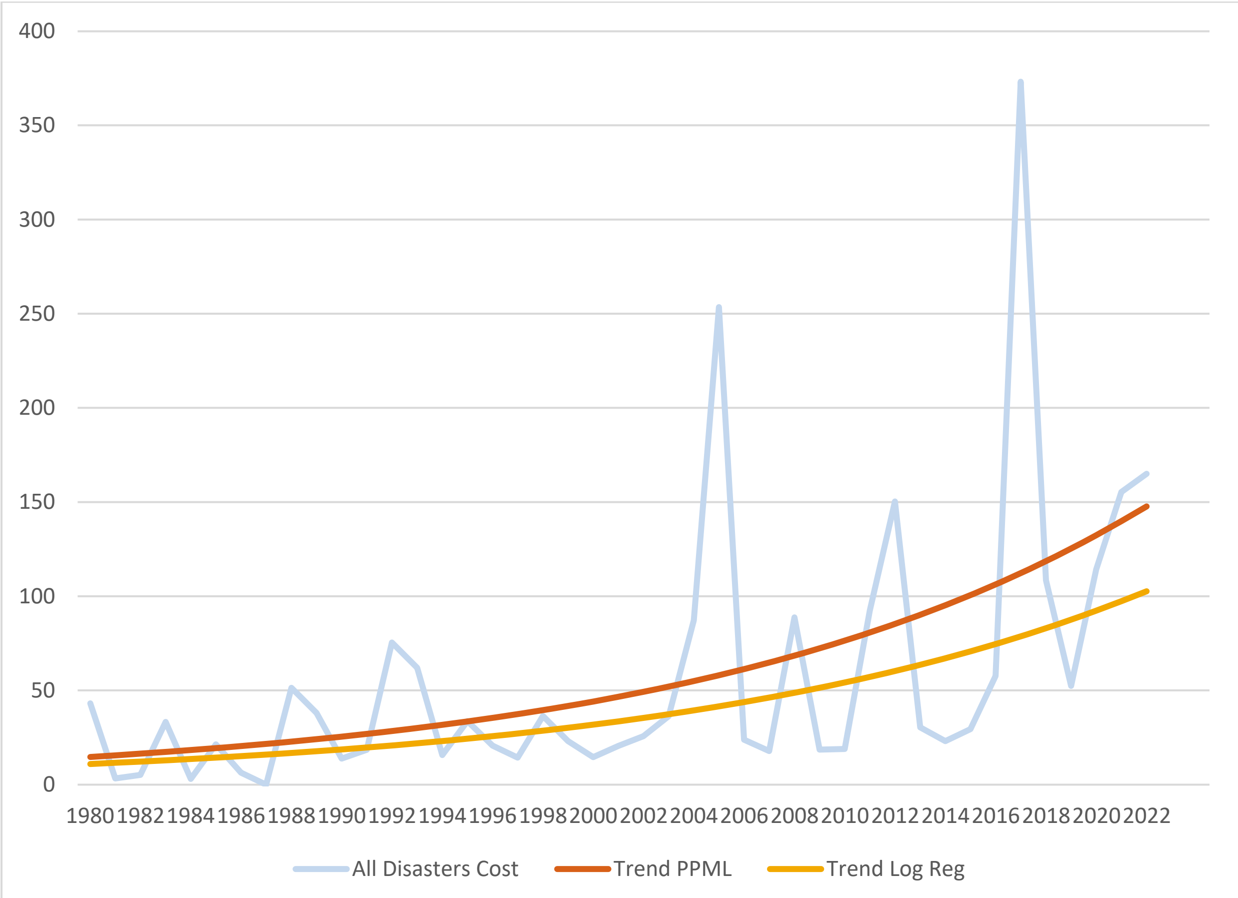


Figure 4. Billion Dollar Weather and Climate Disasters Two Trends and Centered Ten Year Moving Averages

(Billions of 2022 dollars)

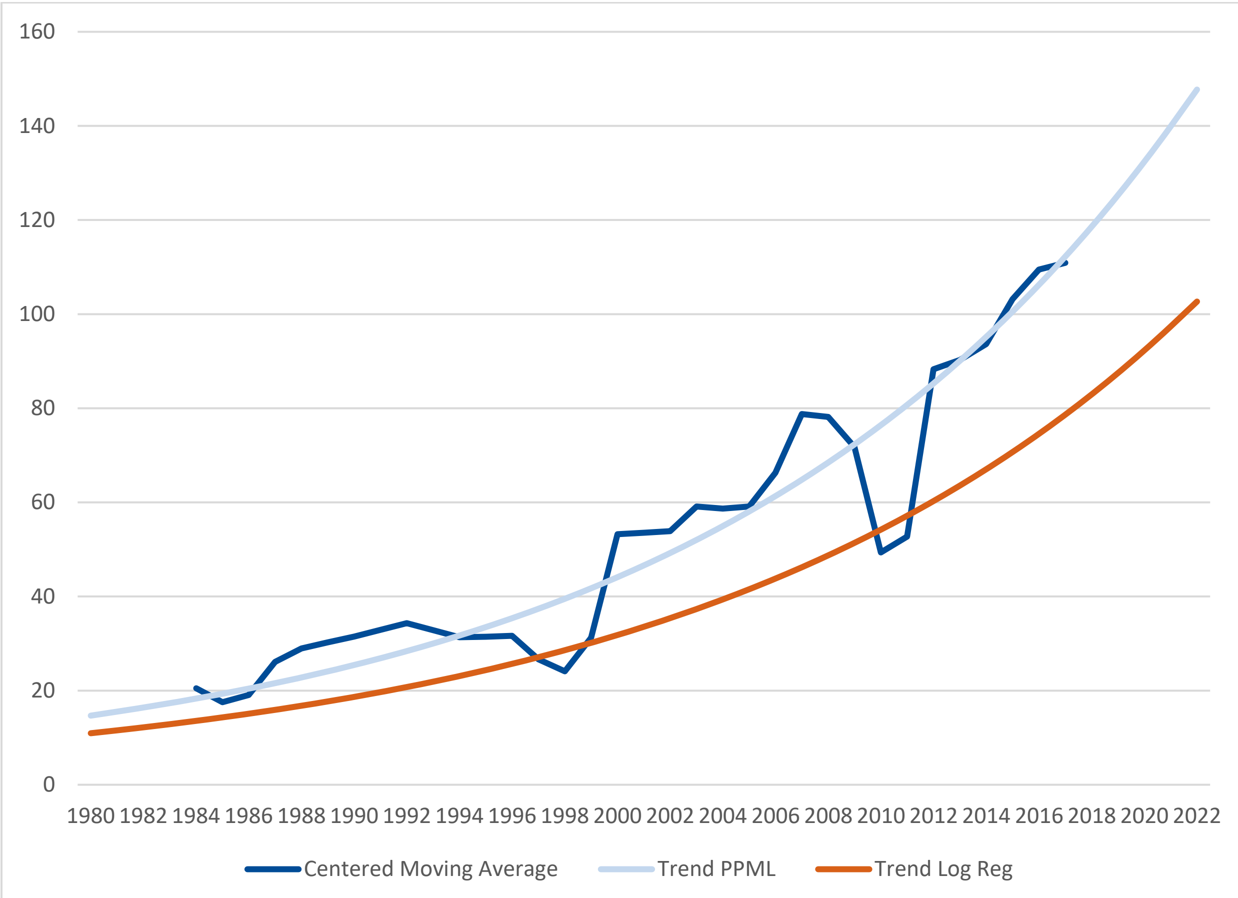
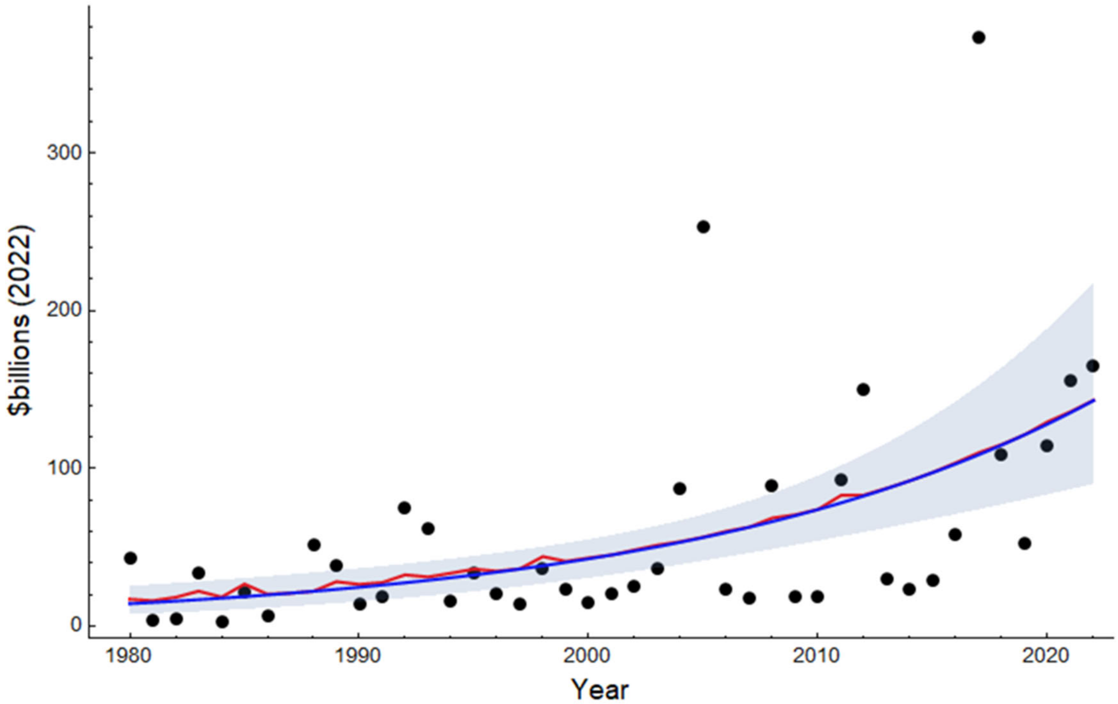


Figure 5. Real Disaster Costs
(Inverse Gaussian Model)



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 Consumer Price Index.

Figure 6. Probability Density Functions of Real Disaster Costs