FEDERAL RESERVE BANK
PHILADELPHIA

Working Papers
RESEARCH DEPARTMENT

Climate Shocks in the Anthropocene Era

Should Net Domestic Product Be Affected by Climate Disasters?

Leonard Nakamura
Emeritus economist, Federal Reserve Bank of Philadelphia Research Department

Brian Sliker
Bureau of Economic Analysis

WP 23-24

PUBLISHED
October 2023

ISSN: 1962-5361

DOI: https://doi.org/10.21799/frbp.wp.2023.24

Climate Shocks in the Anthropocene Era:
Should Net Domestic Product Be Affected by Climate Disasters?

Leonard Nakamura[1]
Federal Reserve Bank of Philadelphia

Brian Sliker
Bureau of Economic Analysis

October 2023

Abstract

The monetary costs of weather and climate disasters in the U.S. have grown rapidly from 1980 to 2022, rising more than 5 percent in real terms annually. Much of this real growth in costs is likely due to climate change. Regardless of its cause, these costs imply a faster depreciation of real assets. We argue that the expected depreciation from these events could be included in the consumption of fixed capital, leading to lower levels, and slightly lower growth rates, for net domestic product (NDP). We use Poisson pseudo-maximum-likelihood regressions to estimate this expectation and to generate our experimental measure of costs. An alternative calculation of depreciation and NDP might be derived from the time series of costs incurred rather than from the far smoother expectation. This latter series might be more appropriate for a national income satellite account. We also investigate the parametric distributions of the annual average-cost and total-cost data.

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

---

[1] Nakamura is an emeritus economist in the Research Department of the Federal Reserve Bank of Philadelphia. Email: leinakam@msn.com. Sliker is an economist at the Bureau of Economic Analysis, U.S. Department of Commerce. Email: brian.sliker@bea.gov. We thank Scott Wentland, Abdul Munasib, Allison Derrick, Marshall Reinsdorf, Rachel Soloveichik, Bryan Parthum, and Wesley Ingwersen for helpful comments on this paper.

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 Anthropocene Epoch. Impacts on the Earth's weather systems through greenhouse gases are an important aspect of this new role of human economic activity. One consequence is a conspicuous and continuing rise in the costs of weather and climate disasters both in the U.S. and around the world. Although how much of this rise is due to climate change and greenhouse gases is an important topic, it is not one we tackle here. Rather, we focus on the apparent increases in the costs of U.S. weather and climate disasters, which are not included in existing measures of asset depreciation and represent an appreciable and growing proportion of depreciation.

Net domestic product (NDP) does not, as currently measured, take into account catastrophic losses. As a result, NDP may not correlate as well with well-being. (NDP is not a measure of well-being; improving its relationship with well-being is useful to the extent that NDP growth is taken as a desideratum of economic policy.)[2] An asset-destroying climate event does not appear as a reduction in NDP, although it does reduce 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.

In this paper, 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 time series of billion-dollar weather and climate disasters (BWCDs) from the National Oceanic and

---

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

Atmospheric Administration (NOAA). Method One is to incorporate the smoothed time series as an expected cost in consumption of fixed capital (CFC), that is, in depreciation, and to 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.

On an industrial level, if the expected losses to insurers are understated because catastrophic losses are not included in them, then their contribution to output may be overstated.

NOAA has constructed a time series of BWCDs in the U.S. from 1980 to the present. It estimates the cost of disaster events amounting to $1 billion in economic losses or more; these are measured in real dollars of the most recent year (which, for the purposes of this paper, is 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 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 2022, 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. Arguably, much of this increase is attributable to climate change, although without detailed attribution analysis, we cannot attribute all of the increase in BWCD costs to climate change. On the other hand, in the Anthropocene, it might be argued that the costs of climate disasters are increasingly an externality of human economic activity, just as pandemics may be. Externalities are indeed no longer as easy for the System of National Accounts (SNA) to ignore as they were in the past.

These disaster costs are, in principle, subsumable under the social cost of carbon and measures of natural capital. However, if these costs rise substantially faster than GDP growth, as they have been, then their capture is not straightforward. The social cost of carbon and measures of natural capital embed assumptions about the future path of these costs, which may not be justified ex post. There are, of course, many costs of climate change and its amelioration that are not included in climate and weather disasters.

We can further argue that the unexpected component of BWCDs, which we agree should be in OCVA, might also usefully be included in a natural capital 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. 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 (Bevere and Orwig,, 2015) and on U.S. weather and climate disasters (Smith and Katz, 2015; 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 IV. 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. The Data from NOAA

NOAA's National Centers for Environmental Information collects data on BWCDs. From its website:[3]

> 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.

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 interruptions 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.

---

[3] See www.ncei.noaa.gov/access/billions/.

The second column in Table 1 shows the number of BWCD events, in which 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. For example, there was originally only one disaster in 1980 that passed the billion-dollar mark: a drought and heatwave in the summer and fall that cost $10 billion. 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 per year that cost $1 billion 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, average annual BWCD costs were $20.5 billion, while in the decade from 2013 to 2022, average BWCD costs were $111 billion, a real compound annual growth rate of 5.3 percent. Chart 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 nonincrease, 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.

IV. Statistical Description of Annual Data

The regression work of the paper in Section V 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,[4] with the consistent but heteroskedastic Poisson pseudo-maximum-likelihood estimator.[5] 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-dollar-plus disaster-cost[6] and *total* billion-dollar-plus 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) and can answer the question of how much sub-billion-dollar disasters matter. Finally, the choice of distribution might bear on Weitzman's 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 ($\mu>0$, $\lambda>0$)
LogLogistic ($\gamma>0$, $\sigma>0$)
LogNormal (μ, $\sigma>0$)
Nakagami ($\mu>0$, $\omega>0$)
Shifted Gompertz ($\lambda>0$, ξ)
0-Shifted Gompertz ($\lambda>0$, ξ)
Weibull ($\beta>0$, $\theta>0$).

---

[4] 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.

[5] See Gourieroux, Monfort, and Trognon (1984) for the original work and Santos Silva and Tenreyro (2006), who implement the Poisson pseudo-maximum-likelihood regression (PPML) in a trade setting after considering some related alternatives.

[6] Just what you'd think: real total billion-dollar-plus costs, divided by the number of billion-dollar-plus events, year by year. This works because NOAA doesn't count costs from events that haven't cleared the billion-dollar disaster threshold.

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 (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 $\beta<1$ but thin otherwise. With only 42 observations,[7] 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 non-nested 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 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 modification to the 0-Shifted Gompertz form imposes a zero density at the origin.[8] There are surely other two-parameter distributions that we've neglected and could be persuaded to fit, subject to diminishing returns.

---

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

[8] 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

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-dollar-plus 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:

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

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

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

Full details of the fits, for these distributions and the other 10, are given in Table 3.[9]

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) 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

---

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: $f(x) = \{\lambda\, (1 + \xi)^2/(\xi + \mathrm{Exp}[-1-\xi])\}\, Exp[-\lambda\, x - (1 + \xi)\, e^{-\lambda x}]\, (1 - Exp[-\lambda\, x])$.

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

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 fits leave much mass below the $1 billion mark: just 0.2 percent of the full Inverse Gamma density and *0.02 percent* of the full Fréchet. NOAA's billion-dollar cut, then, is harmless.

V. National Accounts Methodology

National production accounts are calculated on both a gross and a net basis, the difference between the two being CFC. The question we address here is to what extent CFC 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 244:

> 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 CFC unless they are included in accidental normal damage. From page 123, chapter six (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 because of climate change. If so, perhaps the expected component of these costs should be included in CFC.

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 way the Bureau of Economic Analysis (BEA) treats 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 CFC. 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 Appendix in Chapter 5 of the BEA Handbook of Methods for BEA's treatment of catastrophes for non–life insurance in U.S. personal consumption expenditures.

VI. Measuring Expected Costs

We now turn to the estimation of the expected component of BWCD costs to guide an experimental measurement of CFC.

Experimental measurement of CFC:

Measurement One: Expected catastrophic losses due to climate and weather.

Measurement one uses a log trend to estimate expected BWCD costs and proposes to add these expectations to CFC. To estimate this expectation, we use two types of regressions. The first is a conventional ordinary least squares (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 on time:

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

Regression of log annual BWCDs 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 to either add a dummy variable for that date or replace the zero with one, 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), so that will be our preferred regression as it is most conservative. The output of the regression with a 1 inserted in 1987 costs (so that the log is zero) is Table 4, column 1, which gives a trend growth rate of 5.2 percent annually. The output of the regression with a dummy variable included for 1987 is shown in Table 4, column 2. This gives a trend growth rate of 5.9 percent annually.

One difficulty of using the log trendline as expected loss is that NDP is an additive measure. Under these circumstances, in which 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 Jensen's inequality implies that $E(\ln y) \neq \ln E(y)$ and therefore that the first regression in the presence of heteroscedasticity is not just inefficient but also biased. They suggest using Poisson pseudo-maximum-likelihood estimation techniques to estimate the second regression.

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.

Regression of BWCDs on exponential of time using Poisson pseudo-maximum-likelihood estimation technique. The first advantage of using Regression 2 rather than Regression 1 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 of BWCDs; the output is shown in Table 4, column 3. The trend growth rate is 5.5 percent, between 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 10-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 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 BWCDs and their 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 of NDP. 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 point — in nominal terms, from 5.156 percent to 5.143 percent (note that with the magic of rounding, this is a change from 5.2 percent to 5.1 percent).

The impact on the overall rate of depreciation is more noticeable. Without including BWCDs, CFC as a proportion of NDP goes from 17.6 percent in 1980 to 20.2 percent in 2022. Including the trend in BWCDs, 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 IV, 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 Table 6, at least one time coefficient is not statistically different from zero for 11of the 12 distributions (indicated by gray 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: $\mu_o \operatorname{Exp}[\mu_1(t-2001)]$. The μ_1 term is a complementary estimate of the disaster-induced depreciation rate, whose value, .055 ± .026, is essentially the same as the PPML regression result but accounts for disasters below the $1 billion cutoff. Over the whole 1980 to 2022 period, the estimated left-truncated conditional mean…

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

…averages $138 million less than the (left-truncated) observations — essentially unbiased, within the spread of the data. [10] The root mean squared error of $60.4 billion is in line with other distributions.

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

---

[10] 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. $\mu_o \operatorname{Exp}[\mu_1(t-2001)]$, *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 $\lambda_o \operatorname{Exp}[\lambda_1(t-2001)]$, the time-trending scale term for the Inverse Gaussian distribution. "Erfc" is the complementary error function.

— 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.. Figure 6 reflects changes in the Inverse Gaussian density across the start, middle, and end years of the data, and 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-dollar-plus 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.[11]

Method Two includes 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, one could add the unsmoothed losses from BWCDs and subtract them 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 might thus 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 BWCDs 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

---

[11] All quantitative work behind Tables 3 and 8 and Figures 2, 5, and 6 was performed with Mathematica 12.

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 of the year's total BWCD costs of $313 billion. BWCDs in 2017 were 1.9 percent of NDP, following 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 from devastating storms and fires than the current published series or than Method One. The counterpart would have been a much higher growth rate from 2017 to 2018.

VII. Summary

In brief, this paper outlines two experimental methods for adjusting CFC 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, and not all of these can be attributed to climate change. The underlying data need further work to remove some of the climate and disaster costs that are not destruction in assets.

References

Al Kazimi, Amro, and Cameron A. Mackenzie. 2016. “The Economic Costs of Natural Disasters, Terrorist Attacks, and Other Calamities: An Analysis of Economic Models That Quantify the Losses Caused by Disruptions.” *Proceedings of the 2016 IEEE Systems and Information Engineering Design Symposium (SIEDS)* (April 29), Charlottesville, VA. doi.org/10.1109/SIEDS.2016.7489322.

Bevere, Lucia, and Kiirsten Orwig. 2015. “Natural Catastrophes and Man-Made Disasters in 2014: Convective and Winter Storms Generate Most Losses.” *sigma* No. 02/2015.

Coronese, Matteo, Francesco Lamperti, Klaus Keller, Francesca Chiaromonte, and Andrea Roventini. 2019. “Evidence for Sharp Increase in the Economic Damages of Extreme Natural Disasters." *Proceedings of the National Academy of Sciences*, 116 (43), 21450–5. doi.org/10.1073/pnas.1907826116.

Duan, Naihua. 1983. “Smearing Estimate: A Nonparametric Retransformation Method.” *Journal of the American Statistical Association*, 78 (383), 605–10 doi.org/10.1080/01621459.1983.10478017.

European Commission, International Monetary Fund, Organisation for Economic Co-operation and Development, United Nations, and World Bank. *System of National Accounts 2008*. New York: United Nations, 2009. unstats.un.org/unsd/nationalaccount/docs/SNA2008.pdf.

Gourieroux, Christian, Alain Monfort, and Alain Trognon. 1984. “Pseudo Maximum Likelihood Methods: Applications to Poisson Models,” *Econometrica*, 52 (3), 701–20. doi.org/10.2307/1913472.

Hulten, Charles R., and Leonard I. Nakamura. 2022. “Is GDP Becoming Obsolete? The ‘Beyond GDP’ Debate,” NBER Working Paper No. 30196, July 2022. doi.org/10.21799/frbp.wp.2022.37.

Landefeld, J. Steven, Shaunda M. Villones, and Alyssa Holdren, 2020. “GDP and Beyond: Priorities and Plans,” *Survey of Current Business*, June 2020 Volume 100, Number 6.

NOAA National Centers for Environmental Information (NCEI). *U.S. Billion-Dollar Weather and Climate Disasters* (2023). https://www.ncei.noaa.gov/access/billions/, DOI 10.25921/stkw-7w73.

Reinsdorf, Marshall, Dominique Durant, Kyle Hood, and Leonard Nakamura. 2017. “Improving the Treatment of Holding Gains and Default Losses in the National Accounts,” *Review of Income and Wealth* 63, Supplement 2, December, S321–54. doi.org/10.1111/roiw.12328.

Santos Silva, J.M.C., and Silvana Tenreyro. 2006. "The Log of Gravity." *Review of Economics and Statistics*, November, 88 (4), 641–58.
doi.org/10.1162/rest.88.4.641.

Shukla, Charchit. 2021. “An Analysis of Billion-Dollar Natural Disasters in the United States.” Master’s thesis, Iowa State University. www.imse.iastate.edu/files/2021/11/ShuklaCharchit-thesis.pdf.

Smith, Adam B., and Richard W. Katz. 2013. “U.S. Billion-Dollar Weather and Climate Disasters: Data Sources, Trends, Accuracy and Biases.” *Natural Hazards* 67, 387–410.
doi.org/10.1007/s11069-013-0566-5.

Weitzman, Martin L. 2009. “On Modeling and Interpreting the Economics of Catastrophic Climate Change.” *Review of Economics and Statistics*, 91 (1), 1–19.
doi.org/10.1162/rest.91.1.1.

Weitzman, Martin L. 2011. “Fat-Tailed Uncertainty in the Economics of Catastrophic Climate Change.” *Review of Environmental Economics and Policy*, 5 (2), 275–92.
doi.org/10.1093/reep/rer006.

Weitzman, Martin L. 2014. “Fat Tails and the Social Cost of Carbon.” *American Economic Review: Papers & Proceedings*, 104 (5), 544–6.
doi.org/10.1257/aer.104.5.544.

Table 1. Annual United States Billion-Dollar Disasters (CPI-Adjusted to Billions of 2022 Dollars)					
(1) Year	(2) Number of Disasters	(3) All Disasters Cost	(4) 10-Yr 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

Source: NOAA, NCEI, 2023, *Billion-Dollar Climate and Weather Disasters*.

Table 2. Decade Annual Averages of U.S BCWD Events and Costs, Billions of 2022 Dollars (Based on CPI)			
Decade	Number of Billion-Dollar Disasters	Cost of Billion-Dollar Disasters	Cost per Disaster
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

Source: NOAA, NCEI, 2023, *Billion-Dollar Climate and Weather Disasters*.

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:	**10.8918**	shape2:	**2.479**
			“*p*”	(2.71925)	“*q*”	(.542588)
Birnbaum-Saunders	−119.57	.017	shape:	**.906201**	scale:	**.182144**
			“α”	(.118233)	“λ”	(.025891)
Fréchet	**−115.482**	**1.000**	shape:	**1.6282**	scale:	**3.68885**
			“β”	(.198986)	“θ”	(.368901)
Gamma	−121.937	.002	shape:	.679122	rate:	**.113359**
			“ν”	(.364234)	“δ”	(.0430756)
Inverse Gamma	−115.828	.708	shape:	**2.17369**	scale:	**8.90382**
			“ν”	(.455594)	“δ”	(2.14577)
Inverse Gaussian	−118.128	.071	mean:	**7.68018**	scale:	**8.03213**
			“μ”	(1.16037)	“λ”	(2.11652)
LogLogistic	−117.047	.209	shape:	**2.15336**	scale:	**4.68154**
			“γ”	(.332659)	“σ”	(.601382)
LogNormal	−118.153	.069	log mean:	**1.60533**	log st.dev.:	**.839389**
			“μ”	(.14495)	“σ”	(.114362)
Nakagami	−124.612	.000	shape:	.0176309	spread:	16.1309
			“μ”	(.103573)	“ω”	(89.1938)
Shifted Gompertz	−120.288	.008	scale:	**.08393**	shape:	**−.820207**
			“λ”	(.0226204)	“ξ”	(.186773)
0-Shifted Gompertz	−118.386	.055	scale:	**.0691993**	shape:	**−6.97187**
			“λ”	(.0272583)	“ξ”	(2.07595)
Weibull	−121.325	.003	shape:	**.79129**	scale:	**5.22268**
			“β”	(.151618)	“θ”	(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 nonrobust and for bootstrap standard errors are similar and available upon request.

Table 5. Impact of Costs and Trend of Including BWCDs in CFC, in Nominal Terms

	Billions of Dollars				Percent of NDP				
(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 to 2022	5.2%	5.5%	6.2%	8.5%					

Source: NOAA, NCEI, 2023, *Billion-Dollar Climate and Weather Disasters*, and Bureau of Economic Analysis, retrieved from Haver Analytics.

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:	**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)

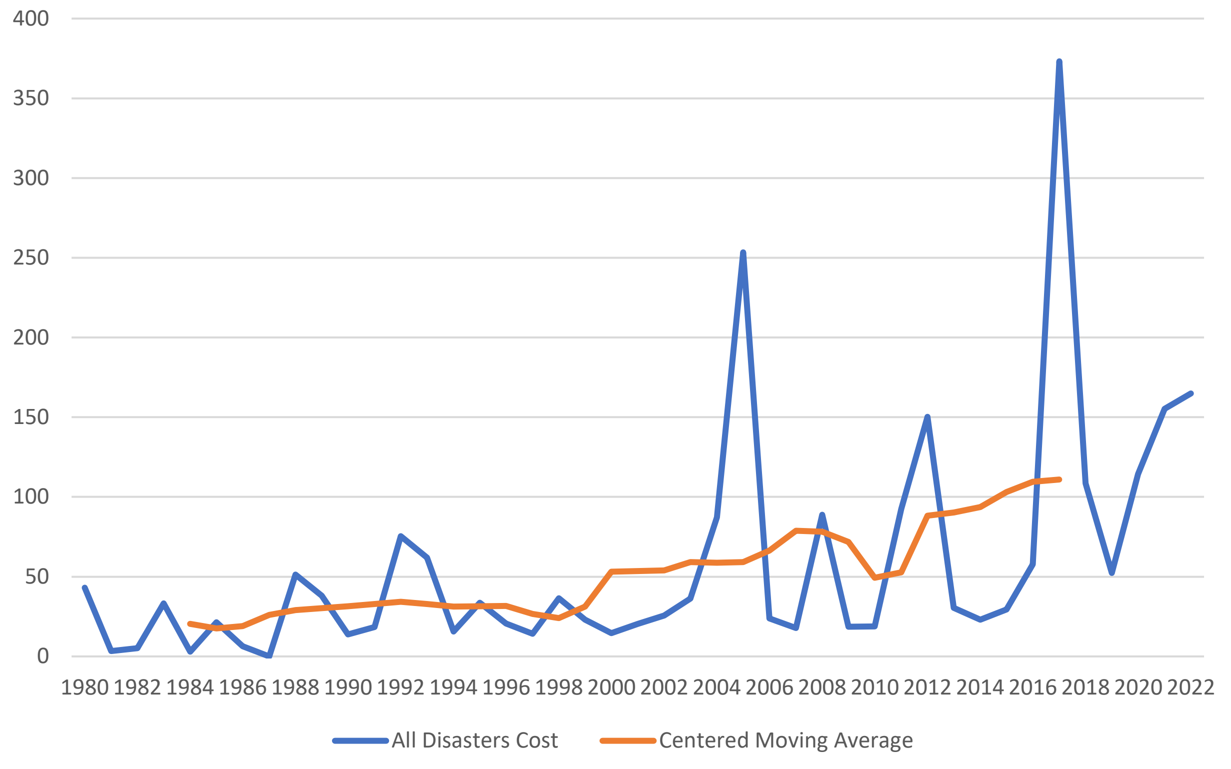
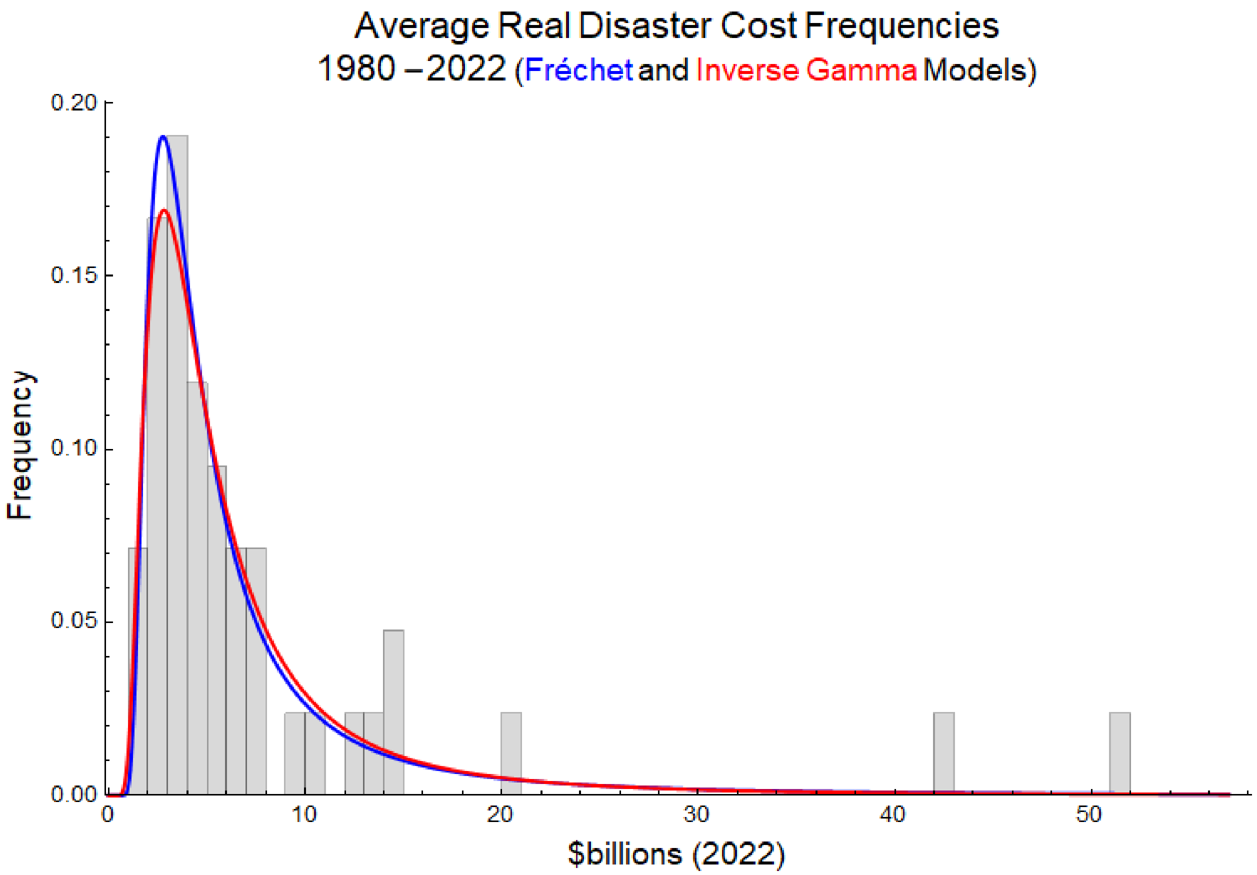


Figure 1. Real BWCD Costs and 10-Year Centered Moving Average (Billions of 2022 Dollars, Deflated by CPI-U

Figure 2



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.

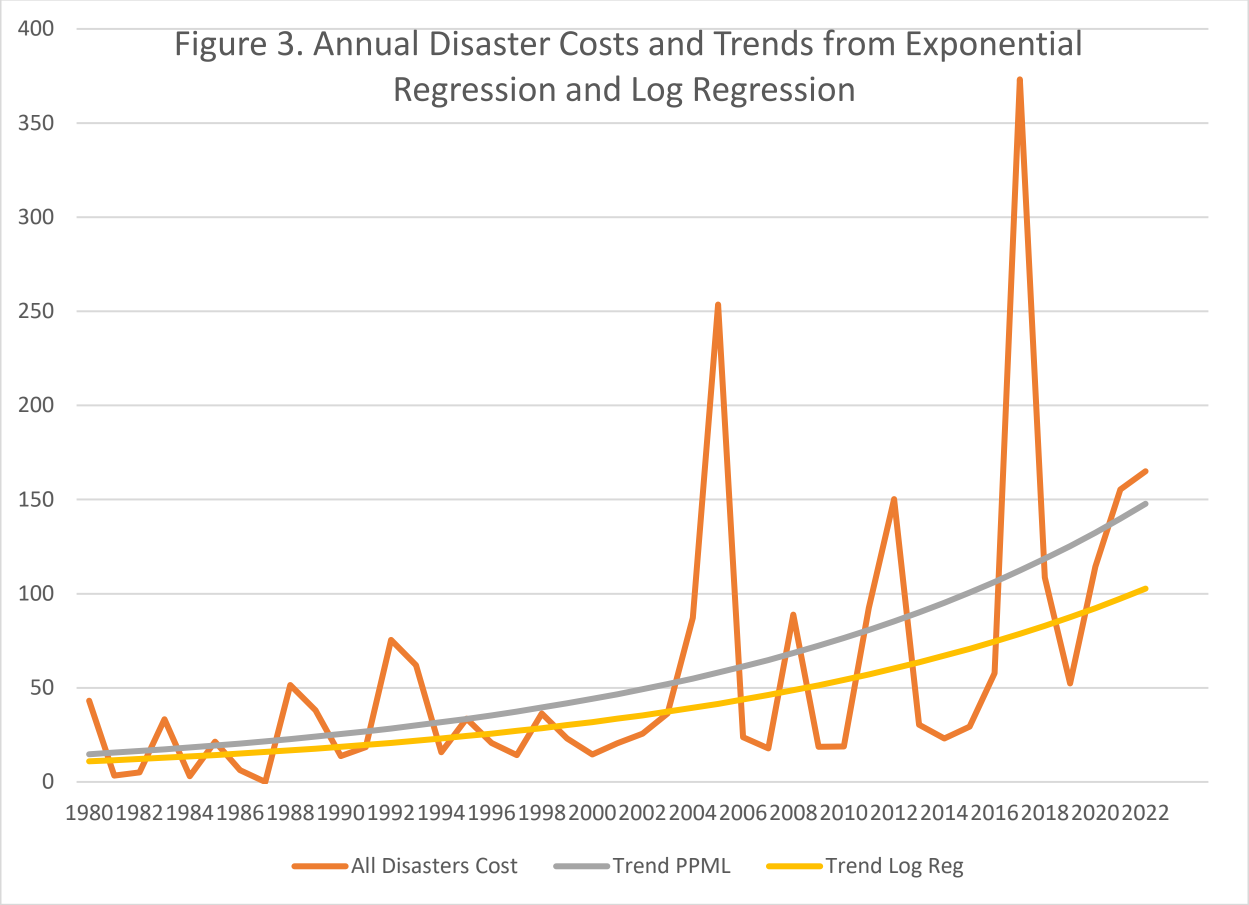


Figure 3. Annual Disaster Costs and Trends from Exponential Regression and Log Regression

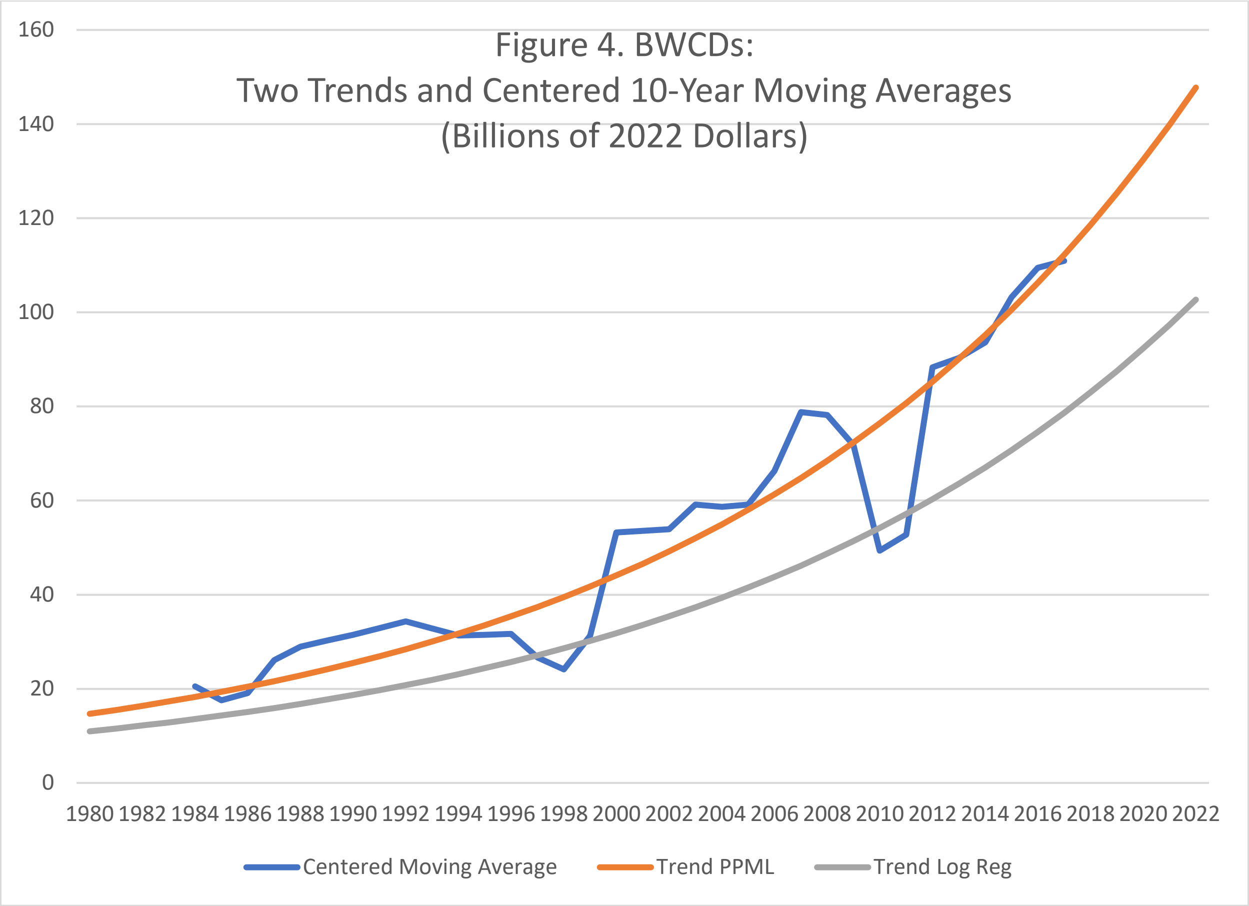
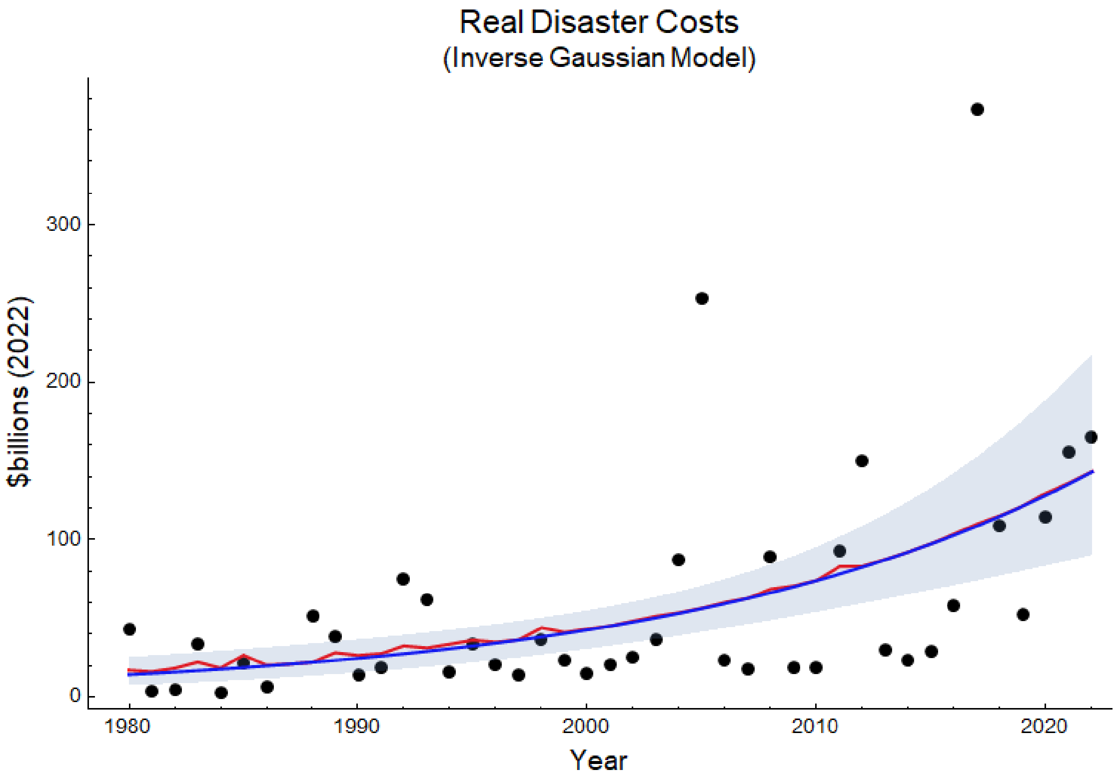


Figure 4. BWCDs:
Two Trends and Centered 10-Year Moving Averages
(Billions of 2022 Dollars)

Figure 5.



Notes:

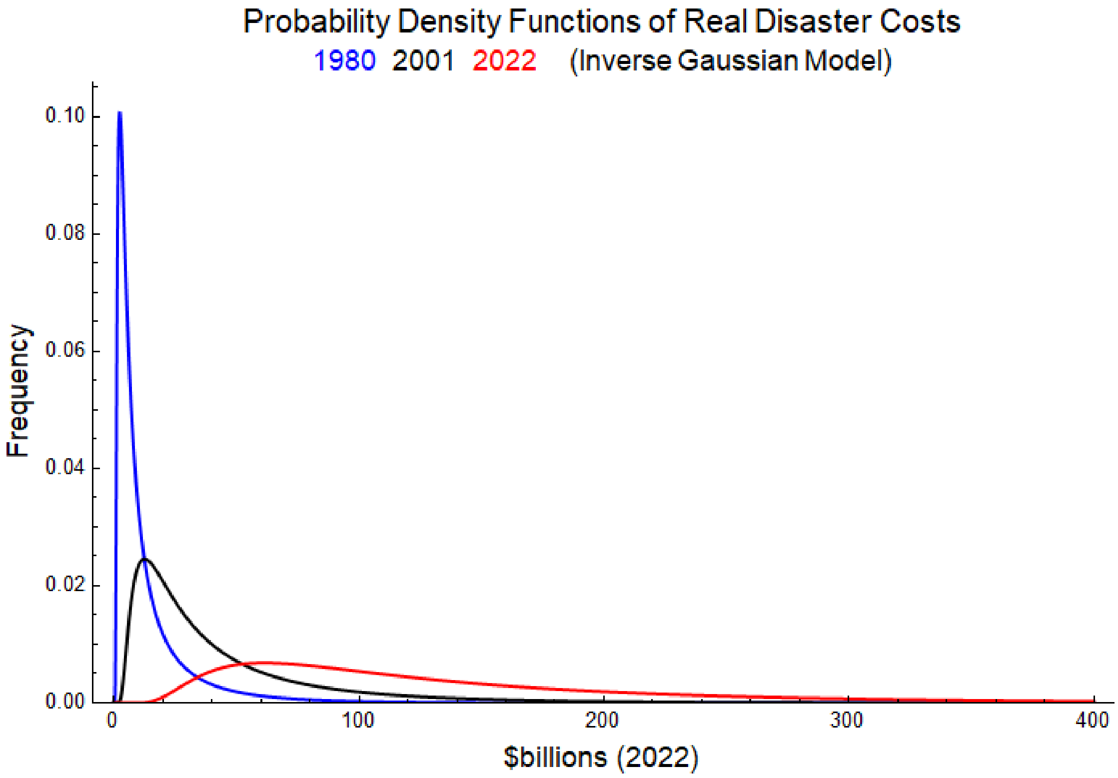
Rough Red Line = fitted left-truncated means (used in calculations of bias and RMSE)

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.

Figure 6.


Probability Density Functions of Real Disaster Costs
1980 2001 2022 (Inverse Gaussian Model)
Frequency
0.10
0.08
0.06
0.04
0.02
0.00
0
100
200
300
400
$billions (2022)