TESTING FOR THE SIGNIFICANCE OF EXTREME WEATHER AND CLIMATE EVENTS ON STATE ECONOMIES

by

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Abstract

Extreme weather and climate events capture significant attention since they often inflict considerable physical damage and loss of personal property. The expectation might be reasonably drawn that these impacts have significant, negative effects on the economies in which the events occur. Using intervention analysis, an attempt is made to explore the economic impact of selected, major extreme weather and climate events of the last decade in the U.S. on the annual gross state products of the states in which the event was observed. In only one case was the state-scale impact statistically significant. In large part, the initial negative impacts of an event are more than offset (economically) by an in-pouring of disaster relief payments from the federal government as well as pay-outs by private insurance companies. Hence, the analysis concludes that a true assessment of the negative economic impacts may require a focus on smaller geographic scales than the states and a further focus on time intervals shorter than one year.

Key Words: Economic impact; intervention analysis; weather and climate extremes.
Subject classification: A2, A3, A4, A5, O2, S1, 3.0, 3.2, 3.4, 4.1.3, 4.2.4, 5.1

1. Introduction

There is growing concern about the ever increasing economic losses from weather hazards in the United States (Mileti, 1999). Numerous weather extremes during the 1990-1997 period produced \$49 billion in insured property and crop losses (Changnon and Changnon, 1999). Federal relief payments for this eight-year period were an additional \$12 billion (Changnon et al., 2000), roughly 25% of the insured loss payments. Further, there has been escalating concern about the growing losses and the burden of federal relief (Sylves, 1998). This led to a major assessment of the values of losses from natural hazards (National Academy of Sciences, 1999), and this report pointed to the general uncertainty over many loss measures, particularly the delayed and tertiary costs, and also the lack of data on the benefits that often accrue from hazards.

A fundamental question raised about economic losses from weather extremes, that are responsible for 80% of all hazard losses (Mileti, 1999), concerns the relative magnitude of these losses within the context of the nation and the states affected. Hazards by their nature bring severe losses at the locale of the impact, but what is the economic significance of these losses from a broader perspective? This paper addresses the question at the state level perspective by assessing several cases of major extremes in recent years at varying geographical locations around the nation.

When extreme climate events occur, there is an immediate interest in the value of the damages sustained. In many cases, these initial estimates reflect the best assessments made by professionals with considerable experience in estimating damages. In other cases, the numbers are contrived, inflated and often unbelievable, especially when placed in a broader context.[1] A second problem is faced when estimating the impacts of disasters, namely the measurement of the economic benefit associated with recovery programs and activities. As noted in the case of the Iowa flood (see Hewings and Mahidhara, 1996), the economic impact of the injection of state and federal disaster payments can often stimulate a local economy to such an extent that the positive benefits ultimately often outweigh the negative impacts of the disaster. However, this accounting does not take into account the very real distress that might occur or the fact that the benefits and costs may not be located in either the same sectors of the economy or the same geographical areas.

In this analysis, an attempt was made to establish whether the impact of climate-related disasters could be ascertained in the economic welfare indices of a state; since time-series analysis is called for, this limited the choice of appropriate economic time series data. In the end, state level gross product (GSP) series were used; these are prepared by the Bureau of Economic Analysis and made consistent with GNP series.

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[1] A case in point may be made by reference to the economic impact of power losses during last summer's heatwave in Chicago. Hewings was called by the news media to provide veracity for the estimate of a loss amounting to $500 million; he pointed out that this represented 1.5 days of the Chicago metropolitan economy's Gross State Product

The formal analysis was conducted with a variant of what has become known in the econometrics analysis literature as *intervention analysis*; a formal description is provided in the section 2 (see Enders, 1995). In essence, intervention analysis seeks to test for a change in the mean of a time series under the null hypothesis that the intervention (in this case, a weather or climate disaster) created no measurable impact on a state's GSP. The impact was assessed through estimation of the significance of federal payments to states after natural events.

The analysis was based on eight very costly weather extremes that occurred during the 1982-1997 period and these events are listed in table 1. They were selected to encompass a variety of conditions, including floods, hurricanes, droughts, and winter storms, and also to select events that occurred in widely different locations across the United States. The total losses ascribed to each event were greater than $1 billion (current dollars) with losses reaching $25 billion for Hurricane Andrew (NCDC, 2000). As shown in table 1, one or more states in which the eight extremes occurred were chosen for analysis.

The date of federal payments (table 1) was used to determine the specification of the dummy variable in the intervention analysis. After the intervention analysis is described in the next section, the evaluation of the significance of federal payments forms the focus of section 3. Section 4 interprets the findings and the paper concludes with a summary and recommendations section.

2. Intervention Analysis

Intervention analysis became popular as a way to measure the impact of radical changes in some activity; in particular, the adoption of metal detectors in airports as a way to deter hijackings could be tested to see whether there were significant differences in the before and after levels of hijackings (Enders, 1995). While an initial test might be to assess the significance of the difference in the means before and after the intervention, the possibility of serial correlation renders this test inappropriate. Hence, the general functional form takes on the following definition:

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and was clearly excessively inflated. Nevertheless, the number was widely reported in the local news media and on national television news that evening.

$$y_t = a_0 + a_1 y_{t-1} + c_0 z_t + \varepsilon_t \qquad |a_1| < 1$$

where:

z_t is the intervention dummy variable, taking on the value 0 in years prior to intervention and 1 subsequently and

ε_t is assumed to be white-noise disturbance.

In the years prior to the intervention, z_t is zero, hence the intercept term is a_0 and the long-run mean of the series is:

$$a_0 / 1 - a_1$$

After intervention, the intercept term jumps to $a_0 + c_0$ (since z_t is now unity); thus c_0 provides a measure of the impact of the intervention and can be tested using *t* tests.

The long-run effect, $c_0 / 1 - a_1$, and the various transitional effects can be obtained from the impulse response function:

$$\left(1 - a_1 L\right) y_t = a_0 + c_0 z_t + \varepsilon_t$$

where *L* indicates the lag operator.

Hence the change in the dependent variable is seen as a function of the intervention (under the assumption that the series is stationary and that the residual is pure white noise). It is also possible, through elaboration of the impulse response function to test whether the responses are damped, oscillating, or ever increasing. However, such determination would only be made in the event that the intervention was shown to be statistically significant.

The general specification of the model used is shown below:

$$\Delta(\text{Ln}\, y_t) = C_0 + d\Delta(Z) + a_1\Delta(\text{Ln}\, y_{t-1}) + a_2\Delta(\text{Ln}\, y_{t-2}) + \varepsilon_t - b_1\varepsilon_{t-1} - b_2\varepsilon_{t-2}$$

where

Δ indicates the change in the variable;

Y is gross state product

Z is the dummy variable

Ln the natural logarithm.

To determine the appropriate lag length we adopted a trial and error approach and settled with the models based on appropriate Akaiki and Schwarz criteria, and Durbin-Watson statistic.
The actual form of the equation used for three states is shown in figures 1-3.

3. Significance of Federal Payments to States GSP after Natural Catastrophes

The time series data set used is the GSP for 1977-1999[2]. For all the states, the log of the data series was used instead of the levels and, in order to insure the stationarity[3] of the data series, a first differencing was required. The results of the estimations were tested for normality of errors using the Jarque-Bera test and they were found to be normal.

Only estimated models with low values for Akaiki information criterion (AIC) and Schwarz criterion (SC) were retained. The identification of time series processes based on the autocorrelation graphs has proven to be a complex task; alternative criteria that allow for an easy model selection and specification have been developed. These criteria focus on the maximization of the log-likelihood functions, among which are the AIC and SC criteria (Akaiki 1974 and Schwarz 1978). In general, the interpretation suggests that the smaller the values, the better specified is the model. For all the estimations, analysis was performed to be sure that the Durbin-Watson (DW) value would be as close as possible to 2. It is important for the DW to be close to 2 in absolute value. The range of the DW statistic is [0,4] and is used for testing the linear association between adjacent residuals. If the DW statistic falls below 2, there is a positive correlation in error terms and if it takes values between 2 and 4, there is negative correlation. If the value of DW statistic is typically around 2, this shows the absence of correlation in errors, implying a good fit of the model.

[2] In millions of 1999 US dollars (Source: Bureau of Economic Analysis, U.S. Department of Commerce)
[3] Essentially, stationarity tests for the stability over the moments of the distribution; a series is stationary if the means and standard deviations are the same for any arbitrary time-length of observations taken within the series.

The significance of Federal payments to the studied states is summarized in table 2. Figures 1 through 3 contain the output of the estimation process for a sample of three states (California, Florida and Illinois). Also shown are the graphs of the residual, actual and fitted values and also the regression equations with a_1 and a_2 representing the autoregressive processes for AR(1) and AR(2) [autoregressors of lag one and two years respectively] and b_1 and b_2 the coefficients for the moving averages MA(1) and MA(2) [with one- and two-year lags]. Not all equations would have full representation on all AR and MA terms. A dummy variable, Z, is introduced; it would take on a value of 0 for years prior to and after federal disaster payments and 1 during the disaster.

4. Interpretation

Each state's graph shows the visual match of the actual changes in GSP and those predicted by the model. Fluctuating around the zero axis is a plot of the residuals (the difference between the actual and predicted changes in GSP). The better the fit of the model, the smaller the amplitude of the residuals. For California (figure 1), they fluctuate around the zero axis except for 1982, 1983 and 1991, years in which the growth rates oscillated (associated with recessions). Note that the fluctuations for Florida (figure 2) appear to dampen over time as the state's overall change in GSP declined from double-digits in the early 1980s to levels more in line with other states by the end of the period. The Illinois results (figure 3) show only minor fluctuations after the 1993 flood.

What intervention analysis seeks to determine is whether the inclusion of the dummy variable provides additional information that would help explain the fluctuations in GSP. In only one state, California, were federal payments significant (and in this case, between 90-95%). The error tolerance shown in table 2 suggests that the intervention (federal payments) was nowhere near close to being statistically significant in any other state. Why did this result occur? Essentially, two major reasons can be offered. First, the size of the payments in many cases was not large in comparison to the annual growth in the state's GSP. Even though the magnitude of the payment was not included explicitly in the regression analysis, the use of the intervention analysis approach enabled statistical testing of any additional fluctuation that may have occurred during years in which federal payments were made. Secondly, there is an important missing variable – the specific geography of the disaster within a state. Were the analysis conducted at the county or aggregations-of-county level, then the payments may have commanded a greater impact in the changes in the level of the sub-state economy, even though the impacts would not have been significant at the state level. In the same way that "all politics are local," a great deal of economic impact analysis is also local in terms of the significance of the impacts. An analogy with the closure of military bases serves to illustrate the point; at the community level, the impact of the closure of Chanute AFB in Rantoul, Illinois resulted in an increase in unemployment into the double-digit range. At the county (Champaign) level, the impact moved the rate from 4.8 to 5.8; at the multi-county level, the rate increased by 0.3 percentage points while at the state (Illinois) level, no measurable impact could be discerned. Hence, while many climate disasters impact broad areas within some states, the impacts often become diluted by the time the analysis is conducted at the state level. Of course, the use of an indicator, such as annual GSP, may mask sensitivity to disruptions to an economy that are concentrated in both time and space.

5. A Summary and Recommendations

The major finding may be stated succinctly as follows: Most of the worst weather and climate extremes of recent years did not significantly affect the economy of the states in which reported damages were high. For various reasons noted in the previous section, the state economies in which the major events occurred are large, diverse and capable of rapid recovery. For example, after the massive 1993 flood, Illinois' GSP grew from $304 billion to $320 billion between 1993 and 1994. Federal disaster payments of $630 million accounted for less than 4% of the $16 billion growth in the state's GSP between those two years. However, the losses were sustained and many payments were made in a much more concentrated time period (over several months) suggesting that annual time scales may be too insensitive to capture the shorter-term disruptive effects from these extreme weather and climate events. For example, in Illinois, if one assumed that the annual growth occurred evenly each quarter and that the flood disrupted activity for one quarter, then federal payments assume a much greater role – over 15% of a quarter's GSP growth.

Hence, future assessment of the economic impact of climate disasters needs to consider the following issues:

- The geographic scope should be directed to the county or multi-county level
- The time-scale should be reduced from annual to quarterly or monthly
- Appropriate *peer analysis* should be conducted

The latter approach would be needed to separate out the effects of the disaster/recovery from general trends in the economy. This is accomplished by comparison of the affected region with one or more peer regions in which no disasters were recorded. Peer analysis attempts to identify "sister regions" based on their economic characteristics, growth rates, relative location and demographic trends. Again, this analysis would be more appropriate at the sub-state level.

Annual data and adoption of a state-level geographic breakdown of the U.S. still provides too coarse a space-time geography to probe the fundamental significance of climate-induced economic impacts. However, it is clear that this is the direction in which the analysis needs to be moved; national-level impact assessments are even more unlikely to reveal significant effects.

References

Akaiki, H.: 1974, A New Look at the Statistical Model Identification, *IEEE Transactions on Automatic and Control-Series AC*, **19**, 716-723.

Bresson, G. and A. Pirotte: 1995, *Econométrie des Séries Temporelles: Théorie et Applications*. Presses Universitaires de France, Paris.

Changnon, S.A. and D. Changnon: 1999, Record high losses for weather disasters in the United States during the 1990s: How excessive and why? *Natural Hazards*, **18**, 287-300.

Changnon, S.A., R.A. Pielke, D. Changnon, R.T. Sylves and R. Pulwarty: 2000, Human factors explain the increased losses from weather and climate extremes, *Bulletin American Meteorological Society*, **81**, 14-19.

Enders, W.: 1995, *Applied Econometric Time Series*. Wiley, New York.

Hewings, G.J.D. and R. Mahidhara: 1996, Economic impacts: lost income, ripple effects and recovery. In S. Changnon (ed.) *The Great Flood of 1993*, Westview Press, Boulder.

Mileti, D.: 1999, *Disasters by Design*. Joseph Henry Press, Washington, D.C.

National Academy of Sciences: 1999, *The Costs of Natural Disasters: A Framework for Assessment*. National Research Council, Washington, D.C.

NCDC (National Climate Data Center): 2000, *Billion Dollar US Weather Disasters 1980-1999*. NOAA. Ashville, NC.

Schwarz, G.: 1978, Estimating the Dimension of a Model, *Annals of Statistics*, **6**, 461-464.

Sylves, R.T.: *Disasters and Coastal Zone States*. University of Delaware, Sea Grant Program.

List of tables and figures

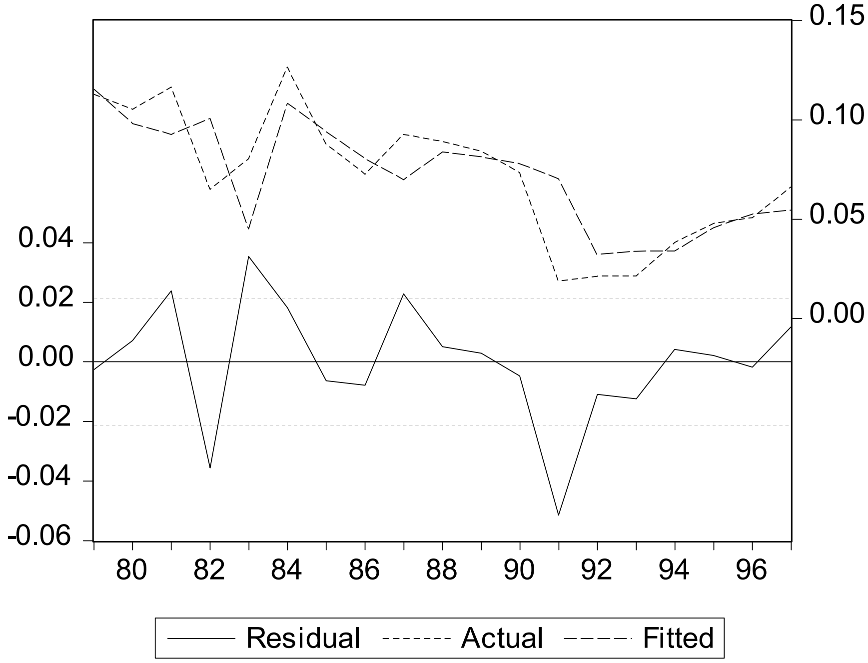
Table 1: Events Analyzed

Event	Dates	States Affected	Federal Payments	Date of Payments
Flood	1982-1983	California	$120m	1983
Severe drought	1988-1989			
		Illinois	$870m	1988-1989
		Iowa	$921m	1988-1989
		Nebraska	$523m	1988-1989
Hurricane Hugo	1989			
		North Carolina	$63m	1989
		South Carolina	$389m	1989
			$9m	1990
Hurricane Andrew	1992			
		Florida	$1.6b	1992
			$41m	1994
			$151m	1995
		Louisiana	$148m	1992
			$2m	1993
Midwest floods	1993			
		Illinois	$630m	1993-1994
		Iowa	$1.7b	1993-1994
		Missouri	$1m	1993-1994
Superstorm	January 1993			
		New-York	$55m	1993
Flood	May 1997	North Dakota	$59m	1997
Floods	1996-1997	California	$69m	1996-1997

Table 2: Summary of Significance Tests

State	Error tolerance	Significant (Yes/No)
California	7.6%	Yes
Florida	51.4%	No
Illinois	53.3%	No
Iowa	64.6%	No
Louisiana	31.3%	No
Missouri	42.0%	No
Nebraska	91.6%	No
New-York	99.3%	No
North Dakota	92.6%	No
North Carolina	35.6%	No
South Carolina	98.7%	No

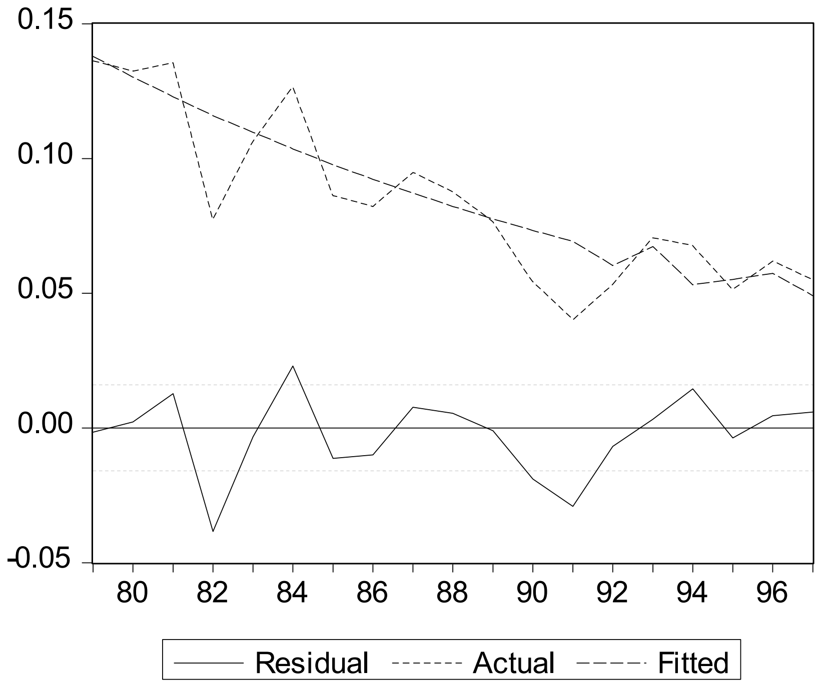
Figure 1: **California**



Dependent Variable: DLOG(CALIFORNIA)
Method: Least Squares
Sample(adjusted): 1979 1997
Included observations: 19 after adjusting endpoints
Convergence achieved after 5 iterations

Variable	Coeff.	Std. Error	t-Statistic	Prob.
C	0.063351	0.017392	3.642536	0.0022
D(CAZ)	-0.019370	0.010209	-1.897399	0.0760
AR(1)	0.700815	0.143847	4.871956	0.0002
R-squared	0.621162	Mean dependent var		0.072157
Adjusted R-squared	0.573807	S.D. dependent var		0.032589
S.E. of regression	0.021275	Akaike info criterion		-4.718598
Sum squared resid	0.007242	Schwarz criterion		-4.569476
Log likelihood	47.82668	F-statistic		13.11719
Durbin-Watson stat	2.139136	Prob(F-statistic)		0.000424
Inverted AR Roots	.70			

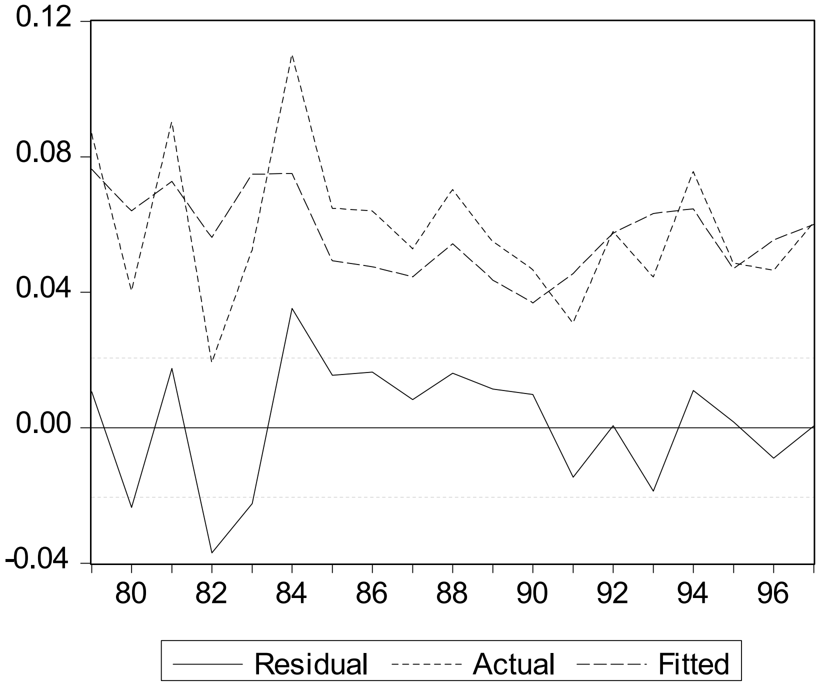
Figure 2: **Florida**



Dependent Variable: DLOG(FLORIDA)
Method: Least Squares
Sample(adjusted): 1979 1997
Included observations: 19 after adjusting endpoints
Convergence achieved after 18 iterations
Backcast: 1978

Variable	Coeff.	Std. Error	t-Statistic	Prob.
D(FLZ)	-0.005331	0.007993	-0.667001	0.5143
AR(1)	0.943966	0.008286	113.9270	0.0000
MA(1)	-0.951425	0.085601	-11.11471	0.0000
R-squared	0.760128	Mean dependent var		0.083963
Adjusted R-squared	0.730144	S.D. dependent var		0.030626
S.E. of regression	0.015910	Akaike info criterion		-5.299837
Sum squared resid	0.004050	Schwarz criterion		-5.150715
Log likelihood	53.34845	F-statistic		25.35113
Durbin-Watson stat	1.914934	Prob(F-statistic)		0.000011
Inverted AR Roots	.94			
Inverted MA Roots	.95			

Figure 3: **Illinois**



Dependent Variable: DLOG(ILLINOIS)
Method: Least Squares
Sample(adjusted): 1979 1997
Included observations: 19 after adjusting endpoints
Convergence achieved after 22 iterations
Backcast: 1977 1978

Variable	Coeff.	Std. Error	t-Statistic	Prob.
C	0.056202	0.004756	11.81654	0.0000
D(ILZ)	0.007723	0.012084	0.639138	0.5331
AR(1)	0.598500	0.103085	5.805893	0.0000
MA(1)	-1.065815	0.276709	-3.851758	0.0018
MA(2)	0.075576	0.295394	0.255850	0.8018

R-squared	0.286261	Mean dependent var	0.058788
Adjusted R-squared	0.082335	S.D. dependent var	0.021460
S.E. of regression	0.020557	Akaike info criterion	-4.710255
Sum squared resid	0.005917	Schwarz criterion	-4.461718
Log likelihood	49.74742	F-statistic	1.403753
Durbin-Watson stat	2.073814	Prob(F-statistic)	0.283434

Inverted AR Roots	.60	
Inverted MA Roots	.99	.08