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ASSESSING THE REGIONAL VARIATIONS OF DISASTER IMPACT IN THE UNITED STATES

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Abstract

This paper utilizes state level data to address the relationship between disasters and economic growth in the United States. Focus is placed on the regional nature of this relationship. The analysis is conducted at two levels: first, utilizing all fifty states to provide a broad model for the entire United States, and second, utilizing only the nine states that define the Northeast United States to generate a more tightly focused single-region model for comparison with the results from the broader national analysis. The results of each model suggest that disasters do affected variations in economic growth and produces differing results for the regional and national models.

Key words:

Disaster, Economic growth, United States, Regional model.

INTRODUCTION

The relationship between disasters and macroeconomic performance is still ambiguous however, several distinct themes are emerging. First, there is existing research on the impacts of disasters that are focused on individual disasters in cities and connected regions, for example, Hurricane Katrina's impact on New Orleans or on the greater Gulf region. These studies have found significant downturns in economic output at the tightly-focused geographic region in the aftermath of the disaster. Ewing et al., (2010) and Gordon (et al., 2010) found that Hurricane Katrina's devastation of the New Orleans area resulted in a downturn in economic output for the city and for the state of Louisiana. Also, studies conducted on the impacts of disasters on small Caribbean nations have found that disasters affect those economies in a negative manner (Barrientos, 2010; Easter, 1999; Rasmussen, 2004). Tsunamis in Japan and Indonesia also resulted in significant reductions in short term economic output (Schipper, 2008).

Second, disasters have also been found to have some potential for positive impacts on affected communities (Ewing & Kruse, 2002; Greenberg et al., 2007; Guimaraes et al., 1993; Skidmore & Toya, 2002). They posit that recovery often demands rebuilding, and these rebuild projects may lead to modernization that generates improvements in efficiency and productivity. The projects may be spurred by businesses as they address recovery after disasters or by governments as they infuse funds in severely affected communities. Economic growth after disaster has sometimes outpaced growth rates before the disasters (Surowiecki, 2011).

Third, there are global studies using countries as the unit of analysis when looking at the impact of disasters on GDP. These have had very inconclusive findings. Altay and Ramirez (2010) found that disasters affect global supply chains, and these impacts differ for upstream versus downstream partners. Kellenberg and Morabak (2008) found measurable patterns between losses from natural disaster and economic development. Numerous other studies have found very little or no substantive results. Noy (2007) review of works on the impacts of macroeconomic disasters found evidence that disasters do involve economic downturns in the short term but noted that this work is in its infancy.

No significant emphasis has been placed on the potential for disasters in one region to affect economic performance in other regions. For example, could a disaster in New York affect other states across the nation, or does a bad hurricane season, largely affecting the Southern states, affect state-level macroeconomics across other states in the nation?

Given the findings from single-state, single-disaster studies and from other studies of global disaster impacts, it appears that disasters are capable of producing both positive and negative outcomes. Global studies appear to be challenged by the fact that these varying impacts of disasters may be offsetting each other, i.e. there may be both negative and positive impacts each occurring in different regions and having offsetting effects. This raises the question of whether the negative impacts found in some studies are simply a matter of cases where the destructive effects of the disasters are greater than the gains from rebuilding and modernization, and are the positive findings the converse of this scenario?

Further, are the resulting impacts moderated by non-disaster related factors? For example, does the economic base of a region, state, or nation matter? Would a manufacturing-intense economy be affected differently than a service-based or agricultural-based economy? Finally, do disasters in one region trigger chains of events that eventually affect GDP in the other regions, and if so, can the relationship between those distant disasters be effectively mapped to local changes in GDP? Were the impacts of Hurricane Katrina limited to the Gulf region or that of Super Storm Sandy to the Northeast region?

Drawing inspiration from the above-mentioned issues, four research questions are posed. First, do disasters account for large movements in GDP, e.g. a 0.5, 0.75 or 1 percentage point movement away from the 5-year moving average? Second, are non-disaster related factors capable of moderating the impacts of disasters on state-level GDP? Third, is economic output affected only by present-year disasters, or do disasters in the previous year contribute significantly to economic impacts? Fourth, do a high number of disasters in one region, say, the Midwest, affect GDP movements in other regions, for example, the Northeast, or are the impacts of disasters confined to the local geographic region?

RESEARCH MODEL

Figure 1 presents the theoretical model for the study. Disasters have macroeconomic impacts. These impacts are moderated by the economic base of the states. The moderating factors are chosen here as the percentages of agriculture, services, and manufacturing/industrial activities in each state for the year in question. This allows for analysis of whether agricultural intense states are affected differently from manufacturing or service oriented states.

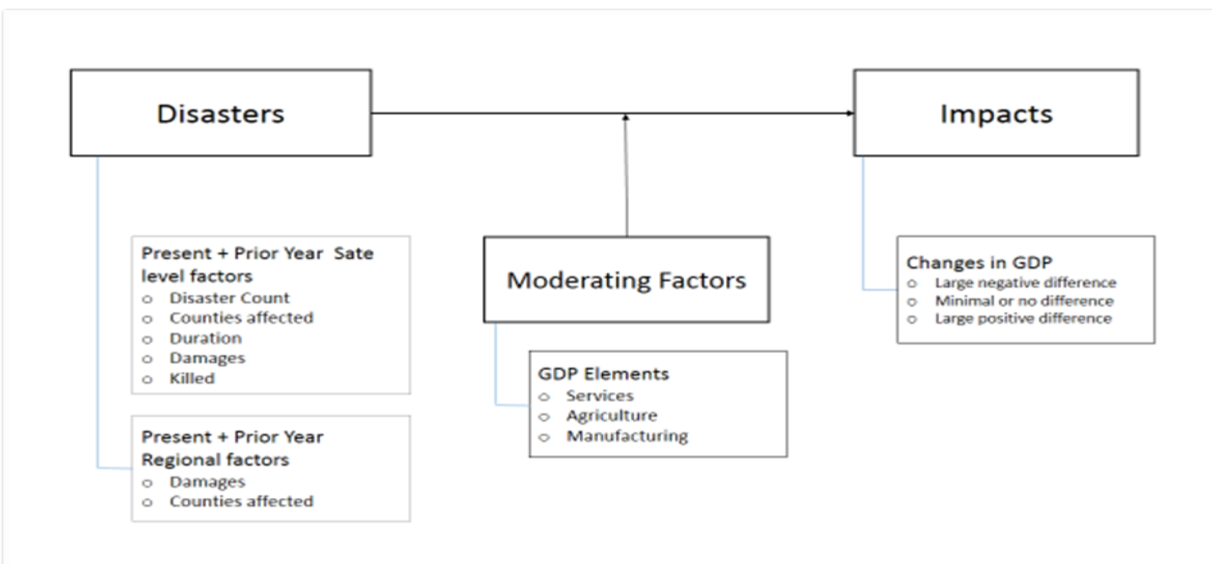

FIG 1. MODEL

Disasters are addressed in two ways:

First, traditional measures utilized in earlier studies are adopted to classify the localized impacts of disasters. The size/scope of the disaster is measured using variables such as count, duration, damages, and number of persons killed. Each of these variables is normalized based on standard conventions (as a percentage of the state's population).

Second, aggregate, regional-level disasters are calculated to facilitate the relationship between disasters in one region and GDP variations in other regions. Two variables, 'damages per region per year' as a percentage of the region's GDP and 'counties affected' per region per year as a percentage of the total number of counties in the region, are chosen for the analysis. Both variables are utilized at present- and prior-year levels (Preliminary analysis of the data pointed to greater significance of these two aggregate variables).

DATA AND METHODOLOGY

Data is taken from two sources:

First, the SHELDUS database managed by the University of South Carolina provides details on the disasters. County-level data is provided on each disaster. This includes start and end dates, injuries, deaths, and monetary value of damages for each disaster for each county in every state. A summary table showing the disaster counts and damages caused is presented in Appendix C. Common disaster types include severe thunder storms, winter weather, flooding, wind damage, and tornadoes. Damages (in 2,000 dollars) totaled $333.8 billion over the period 1991-2008. The data are adapted to reflect the state as the unit of analysis for each year of the study. Disaster data are also available from other sources (For example, FEMA data through www.data.gov). The SHELDUS database provides data on damages that were deemed important to this study, and as such, was chosen as the better source for disaster-related data.

Second, the Bureau of Economic Affairs' (BEA) website provides information for the gross domestic product (GDP) for each state, GDP growth, and the proportion of each state's economy comprised of agricultural-, industrial-, and services-based activities. State-level Real GDP grew at an average of 2.51% over the study period. Agriculture accounted for as little as 0.67% to as high as 2.24% of any state's GDP during the period. Industrial activities accounted for as little as 9.01% to as much as 34.07% of a state's GDP. Finally, services accounted for as little as 67.1% to as much as 80.13% of a state's GDP.

Independent Variables

The list of independent variables is shown in Table 1. Variables are addressed at the present- and prior-year level. The thesis here is that impacts of investments in recovery and rebuilding are an important part of disaster analysis and its impact on GDP. Prior-year events influence the process of recovery, and as such, the positive impacts such as productivity improvements that are often associated with disasters. There is no precedence for the utilization of one versus multiple years of prior disasters to examine productivity improvements or the likely macroeconomic effects. The decision to include the prior year's disaster is, however, deemed essential here.

TABLE 1. DESCRIPTION OF THE STUDY VARIABLES

Abbreviation	Full description	Level
StateYear	Unique identifier: each state for each year of the study (e.g. California 2001)	State
Agriculture	Percentage of State GDP Output generateg from agricultural related activities	State
Munafacturing	Percentage of State GDP Output generateg from Industrial/munafacturing related activities	
Services	Percentage of State GDP Output generateg from services	
Count-sqMi	Number of disasters per square mile	State
Count-pop	Number of disasters per 100,000 persons residents	
Affected	Percentage of counties affected that year	
Duration	Sum of ((counties affected) * (number of days)) /(no of counties in the state)	
Damages	Damages / State-GDP	
Injuries	Injuries / State Population	
Deaths	Deaths / State Population	
MWCouAffected	(Number of Midwest counties affected) / (number of counties in the midwest)	Regional Aggrergrate
MWDamages	(Damages in the midwest) / (GDP for midwest region)	
NECouAffected	(Number of northeast counties affected) / (number of counties in the northeast)	
NEDamages	(Damages in the northeast) / (GDP for northeast region)	
SouCouAffected	(Number of South counties affected) / (number of counties in the south)	
SouDamages	(Damages in the south) / (GDP for midwest south)	
WestCouAffected	(Number of West counties affected) / (number of counties in the west)	
WestDamages	(Damages in the west) / (GDP for west region)	
RealGDP	Real GDP (year = 2000)	State
5YRavge	5 year moving average of GDP (does not include present year)	State
gdp-Diff	Difference between real GDP and the 5 year average.	State
Class	0 = large negative deviation, 1 = very little ir no deviation; 2 = large positive deviation	State

Disasters are analyzed at the state level in terms of disaster counts, duration, damages caused, and number of persons killed. The database does not report persons affected (often assessed in disaster impact analysis). Disasters are reported at the county level allowing us to generate a measure of the affected base for each disaster. The percentage of counties affected by the disaster is utilized as a measure of its impact on the state. For example, one disaster may affect all counties in the state while another affect only a modest fraction of the counties.

The variables are normalized as conventionally done in disaster-related literature. Of note is the normalization of 'Disaster counts'. This is processed in two ways - the number of disasters per 100,000 residents and the number of disasters per square kilometer. Both means of normalizing disaster counts are commonly used in the existing literature. The 'Feature Selection' option in Statistica 10.0 identifies which variables are more significant to the analysis in question. In no cases were both of these normalized variables found to influence the analysis. The full listing of variables and normalizations is presented in Appendix A.

Dependent Variables

GDP change is addressed as a three-tiered, dependent variable, namely, negative GDP change, very minimal change, and positive change relative to the 5- year moving average. There is no precedence in the existing for the level of change utilized as the thresholds. Three unique levels were studied to see the extent to which the predictability of the model changes with the differing thresholds values. The first case utilized a 0.5% threshold. Here, the dependent variable was categorized as:

i. Negative GDP change greater than -0.5 percentage points as "0";

ii. GDP change between -0.5 and 0.5 as a "1"; and

iii. GDP change greater than 0.5 as "2".

The second and third case used thresholds of 0.75% change and 1% change, respectively. The final results are discussed for the level with highest predictive accuracy.

		Predicted		
		0	1	2
Actual	0	Y	X	X
	1	X	Y	X
	2	X	X	Y

FIG 2. CLASSIFICATION MATRIX

As shown in Figure 2, the accuracy of the resulting neural network will be a measure of the extent to which it predicts the 0's, 1's and 2's accurately as 0, 1, and 2 in the test data.

The Neural Network

As presented by Panda and Narasimhan (2007) neural networks do present advantages over other linear and non-linear modeling techniques. Their flexible nonlinear mapping capability allow them to continuously approximate measurable functions with good degrees of accuracy. Also, being nonparametric and data driven they impose very few constraints on the underlying process from which the data is generated. These positives have led to broad usage in fields ranging from medical applications (Kaur & Wasan 2006), to bankruptcy modeling (Wilson & Sharda 1994), exchange rate modeling (Jamal & Sundar 1998) and sales forecasting (Lau et al., 2012).

Neural networks do however have their weaknesses. Minor changes in configurations, number of neuron and/or hidden layers sometimes lead to great changes in the output results. Changes in weightings associated with input variables can also affect results. To overcome these problems we utilized the defaults settings in Statistica's neural network.

The analysis is conducted using the neural network functionality in Statistica (v. 12.0). Unlike many stand-alone neural network software packages, Statistica provides default options for the data analysis with information such as the number of layers and hidden neurons. The algorithms used in the optimal models are provided as a part of the package. Changes may be made to these default settings; however, numerous preliminary runs found very little changes in the output when the defaults settings were adjusted. As such, the decision was made to adopt the default settings as the study's runs were executed. It should be noted that these defaults are not static. A larger dataset will default to a larger number of internal neurons, for example. The net result here is that it moves the discussion away from the extent to which the network is tailored and squarely to the actual output of the networks.

Statistica divides the presented data into three blocks: seventy percent for training the network, fifteen percent for testing the network, and the final fifteen percent for validation of the trained network. The network is trained and tested interactively. This minimizes the risk of the training process getting tied to a suboptimal path with great training output but poor testing results. This interactive training and testing delivers a model that is then validated against the final 15% of the data. This becomes the unseen data against which the predictability of the network is tested. As such, the quality of the final results is attained from the validation performance.

FINDINGS

The model generates an output for each of the three levels of the dependent variables, namely percentage changes to GDP at the "0.5", "0.75", and "1" levels. The predictability results for the entire U.S. and for the Northeast region are shown in Table 2. As stated earlier, Statistica trains and tests the network during development, and the final test of the network performance is the validation performance. This is done against a sample of the data that is held out for assessing the network quality (and is not seen by the training and testing procedures). As such, the validation performance is the critical output for us.

The USA analysis, i.e. fifty state dataset, generated validation performance of 61.4 when using GDP change of 0.5% as the threshold. This validation performance falls to 58.77 and 57.89 when GDP change is held at the 0.75 and 1%, respectively. The validation performance is much higher for the Northeast states. At the 0.5 and 0.75 GDP change thresholds, the model delivers validation performance of 81.82%. This falls to 77.27 for the 1% change in GDP. Given that both national and regional-levels of analysis have optimal results at GDP change of 0.5%, the rest of the study findings will focus only on this set of network outputs.

TABLE 2. VALIDATION PERFORMANCE FOR THE NEURAL NETWORKS

Region	GDP Movement	Network Name	Training Performance	Test Performance	Validation Performance
USA	0.50	MLP-15-9-3	65.18	59.65	***64.10***
	0.75	MLP-15-16-3	66.85	65.79	58.77
	1.00	MLP-11-4-3	54.19	63.19	57.89
NE	0.50	MLP-12-12-3	82.08	81.82	***81.82***
	0.75	MLP-12-10-3	88.68	77.27	81.82
	1.00	MLP-12-8-3	72.64	59.09	77.27

Table 3 shows the classification output for both USA and NE states. As seen on the left the model predicts the USA (50 states) fairly well, but not exceptionally. The '0s' and '2s', i.e. the large negative and positive deviations from 5-year average GDP, are handled much more accurately than the cases that did not fluctuate significantly from the 5-year moving averages. The NE state generates much higher quality results. Predictions are excellent for the '0s' and '2s' and marginal for the '1s'. The '2s', for example, are predicted accurately 100% of the time (nine of nine cases).

TABLE 3. CLASSIFICATION OUTPUT FOR USA AND NE STATES AT 0.5% CHANGE IN GDP

USA		Classified as			
		0	1	2	Total
Actual	0	**28**	0	7	35
	1	12	**3**	6	21
	2	17	2	**39**	58
	Total	57	5	52	

NE		Classified as			
		0	1	2	Total
Actual	0	**7**	3	0	10
	1	1	**2**	0	3
	2	0	0	**9**	9
	Total	8	5	9	

The ROC Curves

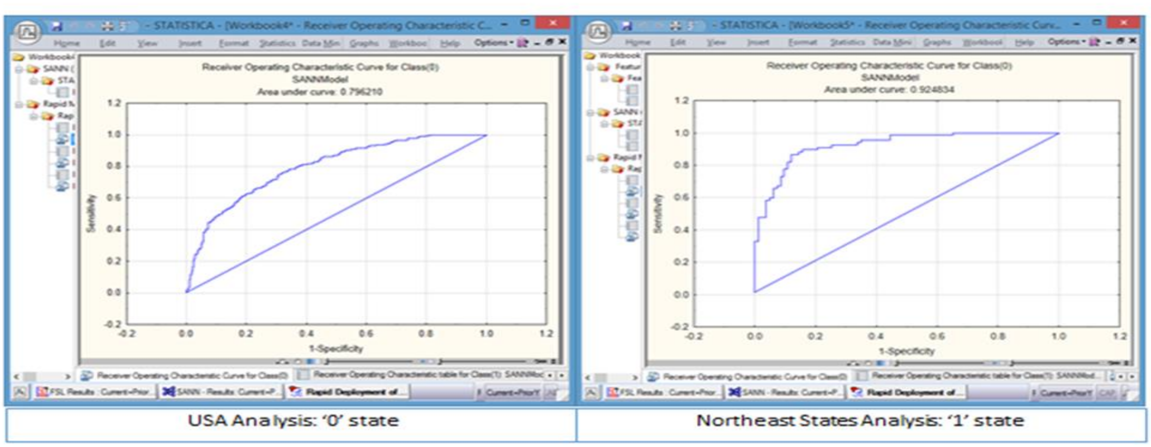

FIG 3. THE ROC CURVES FOR THE (0) STATES FOR USA AND NORTHEAST STATES

A sample of the receiver operating characteristics (ROC) curve is presented in Figure 3. The ROC curves show the accuracy of classification (i.e. percent of true positive to false positive for the model). The choice of a 3X3 matrix, rather than the more conventional 2X2 matrix used in most neural network analyses, resulted in three unique ROC curves generated by the software. Figure 2 presents the ROC curves for the '0s' for both the full USA analysis and the Northeast states analysis. The full set of figures is available in Appendix C.

The area under the ROC curves varies from 0.5 to 1, with 0.5 representing no discrimination and 1 representing perfect discrimination (Flaherty & Patterson, 2003). As seen in Figure 2, the area under the ROC curves for the USA and Northeast states were 0.8 and 0.92, respectively, for the '0' classification. The values for the '1' classification for the USA and NE states analyses were 0.71 and 0.81, respectively. The values for the '2' classification for the USA and NE states analyses were 0.82 and 0.95, respectively. A summary of the ROC values is presented in Table 4.

TABLE 4. FULL LIST OF ROC CURVE VALUES

	USA	Northeast
(0)	0.80	0.92
(1)	0.71	0.81
(2)	0.82	0.95

The Independent Variable Rankings

Statistica produces a measure of the importance of the independent variables to the neural network analysis and ranks the variables by chi-square value. Each chi-square and p-values are provided for each variable entered into the analysis. These results are presented in Tables 5 and 6. As seen in the tables, the aggregate variables dominate the model. They account for the top eight variables in the national study and the top 6 in the more focused Northeast study. Of note is the fact that the same variables do not dominate the two separate analyses. The 'percentage of Northeast counties affected in the prior year' leads the national analysis. This is followed by the 'percentage of Midwest counties affected in the prior year' and the 'percentage of Southern counties affected in the present year". The top three variables for the Northeast regional study are: the 'percentage of West counties affected in the present year', the 'percentage of West counties affected in the prior year' and the 'percentage of Southern counties affected in the prior year'.

Several patterns emerge in the results in addition to the dominance of regional aggregates over state-level variables:

First, both present- and prior-year variables are significant in the models.

Second, the 'percentage of counties affected' variable ranks higher than the 'damages as a percent of GDP' variable. In other words, while both variables are important, the macroeconomic effect of disasters is more closely tied to the number of counties affected by the disasters than by the level of damage caused by the disaster.

TABLE 5. SIGNIFICANCE OF THE INDEPENDENT VARIABLES FOR USA ANALYSIS

Rank	Variable Name	Chi-square	p-value
1	Percentage of Northeast counties affected in prior year	148.89	0.000000
2	Percentage of Midwest counties affected in prior year	137.40	0.000000
3	Percentage of Southern counties affected in present year	118.89	0.000000
4	Damages in Midwest counties in present year	118.06	0.000000
5	Percentage of Midwest counties affected in present year	112.83	0.000000
6	Percentage of Southern counties affected in prior year	109.90	0.000000
7	Percentage of West counties affected in present year	97.67	0.000000
8	Percentage of Northeast counties affected in present year	92.03	0.000000
9	Level of Services in the state's economy	89.75	0.000000
10	Damages in Midwest counties in prior year	80.92	0.000000
11	Damages in Northeast counties in prior year	76.50	0.000000
12	Percentage of West counties affected in prior year	71.99	0.000000
13	Damages in West counties in present year	66.67	0.000000
14	Damages in Northeast counties in present year	47.63	0.000021
15	Number of disasters per 100,000 residents	49.34	0.002750

TABLE 6. SIGNIFICANCE OF THE INDEPENDENT VARIABLES FOR NORTHEAST ANALYSIS

Rank	Variable Name	Chi-square	p-value
1	Percentage of West counties affected in present year	64.98	0.000000
2	Percentage of West counties affected in prior year	61.86	0.000000
3	Percentage of Southern counties affected in prior year	55.25	0.000000
4	Damages in Midwest counties in present year	56.59	0.000000
5	Percentage of Northeast counties affected in present year	55.63	0.000001
6	Percentage of Midwest counties affected in prior year	59.09	0.000001
7	Level of Services in the state's economy	66.01	0.000003
8	Damages in Midwest counties in present year	40.66	0.000013
9	Percentage of Northeast counties affected in prior year	53.52	0.000022
10	Percentage of Southern counties affected in present year	37.88	0.000161
11	Damages in Midwest counties in prior year	29.61	0.000990
12	Damages in Northeast counties in prior year	35.24	0.001354
13	Level of Agriculture in the state's economy	37.09	0.005105

> Third, while 'percentage of counties affected' dominates the study, the variables do change as the unit of the analysis changes. The 'percentage of Northeast counties affected in the prior year' leads the national analysis, while 'the percentage of West counties affected in the present year' leads the Northeast analysis. Also only thirteen variables are significant in the Northeast analysis, with twelve producing the optimal model, while there are fifteen variables in the optimal model for the national study, and all fifteen are significant at the 0.01 level.

The state-level variables were led by the 'percentage of service in the state's GDP'. This was the only state-level variable in the optimal model for the Northeast study and was ranked seventh. The contribution of agriculture to the state's GDP was also significant but not a part of the optimal model. There were two state-level variables in the fifteen that defined the optimal model for the national analysis. The 'percentage of service in the state's GDP' was ninth, and the 'disaster counts per 100,000 residents' was fourteenth.

DISCUSSION

Steady, modest growth in GDP is the assumed state for geopolitical regions. This growth can be managed in many ways. The goal of this study was not to predict exact GDP growth, e.g. will state-level GDP vary from the moving average by 0.25 vs. 0.30 percentage points. Instead we addressed the larger movements in GDP. Can disasters account for large movements, e.g. 0.5, 0.75 or 1 percentage point movement from the 5-year moving average? Further the model addressed both large negative and large positive movements from the 5-year moving average.

While most neural network models are constructed as a 2x2 matrix, the nature of this analysis demanded a 3x3 matrix. The 3x3 matrix naturally delivers a greater number of cells, potentially containing false positive and false negative results, and, as such, usually has somewhat lower prediction rates than most 2x2 models. Nevertheless, the ROC (Figure 2 and Table 4) shows that the predictability of the model is good. Furthermore, they support the thesis that a more focused study delivers significantly higher quality results than broadly defines studies namely, the regional level versus the national level. ROC measures are 10 percentage points or higher for the Northeast analysis compared to the national analysis. The study findings support the ability of the model to strongly predict GDP movements for the Northeast states and to moderately predict GDP movements for the greater United States.

The ROC data shows the effectiveness of the model of predicting both large positive and negative movements in GDP relative to the 5-year moving average. For the Northeast analysis, large positive and negative fluctuations in GDP have ROC values of 0.95 and 0.92, respectively. Cases with little or no fluctuations in GDP have ROC values of 0.82

(Figures in Appendix B). While the predictability is lower for the USA model, the pattern is the same.

The ability to predict the GDP fluctuations is also presented in Table 3. All nine of nine large positive variations (classified as 2's) are correctly classified. Seven of ten large negative variations are properly classified (as 0's), with three classified as 'no significant fluctuation (i.e. 1's). It should be noted that no large negative fluctuations were misclassified as large positive fluctuations, and similarly, no large positive fluctuations were misclassified as large negative fluctuations. In addition, cases classified as large negative fluctuations were correct seven of eight times, and cases classified as large positive fluctuations were all correctly classified. In other words, the disaster-related variables effectively predicted both large negative and large positive fluctuations in state-level GPD from the moving average.

There are obvious differences in the variables affecting the Northeast analysis and those affecting the national analysis. This suggests that there is not a definitive set of variables that affect the relationship between disasters and macroeconomics at a universal level. As such, comparative regional analyses should be expected to uncover a different collection and/or ranking of variables for each region. Larger scale analysis, especially global studies, face the risk of these differing local models offsetting each other and failing to deliver conclusive results.

Most previous studies on the subject matter have largely focused on the individual country data in a global analysis. The findings here suggest a need for three adjustments:

First, regional aggregate variables do influence the relationship.

Second, narrowing the focus of the studies, for example, to continental regions rather than global-focused studies should help the classification models.

Finally, focus needs to be placed on the impacts of disasters in one region on the GDP movements of nations in other regions.

A research question addressed whether non-disaster related factors are capable of moderating the impacts of disasters on state-level GDP movements. Of the three moderating factors only percentage of services in the state's economic mix was found to be significant. This held for both the regional and national models as shown in Tables 5 and 6. Percentage of agriculture and percentage of manufacturing in the state's economic mix were not found to be significant.

Another research question asked whether economic output is affected by previous year disasters or simply by disasters in the present-year. In both the national model and the Northeast region model, present-year and prior-year variables were found to impact movements in GDP. In both models, six prior-year variables accompanied the present-year variables in the optimal model. While the influence of the present-year variables on GDP movements is expected, the large number of prior-year variables suggests that economic impacts of disasters often lags the disasters themselves. The present-year and prior-year variables in the Northeast model are predominantly variables related to regions outside of the Northeast, as discussed below.

The actual state-level disaster-related variables are largely missing in both the national model and the Northeast model. Only one variable, 'disaster counts per 100,000 residents', was significant in the national analysis. There were no state-level, disaster-related variables in the optimal model for the Northeast region. Only 'percentage of counties affected in previous year' showed up in the top fifteen variables. This had a p-value of 0.038 and was not a part of the twelve-variable optimal model. The finding that actual disaster-related state-level variables minimally contribute to the optimal model's prediction capability may be the result of the much larger impact of other regions' disasters.

Finally, we asked whether a high number of disasters in one region, say, the Midwest, affect GDP in other regions, for example, the Northeast, or are the impacts of disasters confined to the local geographic region. Our findings support the thesis that disasters in one region do affect GDP in other regions and states in those regions. As shown in Table 4, the 'percentage of West counties affected by disasters in the current year' was the leading variable for the Northeast analysis, but not, interestingly, one of the Northeast states' own aggregate variables. In addition, the highest-ranked Northeastern aggregate variable is fifth in rank, namely, the 'percentage of Northeast counties affected in present year', while the top four ranked variables relate to regions outside of the Northeast. The dominance of other regional aggregate variables over state-level aggregate variables is surprising. It seems to suggest that single regions within a well-developed, interdependent economy could feel the negative or positive impact of disasters in other regions more than their own regional disaster impact. Whether this is the result of supply chain development, regional specialization, or some other structural effect cannot be determined in this study, but it is an unexpected phenomenon that should be explored in future studies.

CONCLUSION

The study findings support the thesis that disasters are capable of causing movements in GDP. This is in line with earlier findings that disasters affect the GDP of small nations and that disasters do have supply chain implications. Little impact has been shown on the economies of larger nations. In fact, the conclusions from these studies suggest that the economic impacts of disasters on smaller nation are not mirrored in larger economies such as the United States. The findings suggest that disasters affect the economies of larger nations, but that these impacts are observable at smaller, regional levels for example at the state level in the United States.

The findings also suggest the need to look at the impacts of disasters scenario in other regions on the macroeconomics of the region under analysis. This has implications for global studies. Will disasters in the one continent, e.g. Asia, affect macroeconomics in other regions, e.g. Europe or North America? There is also a need for further work in calibrating the relationships in other regions. The findings here address the differences in quality of results between a focused Northeast analysis and a full 50-state US analysis. The nature of the relationships in other regions may also need to be calibrated. Further, does a parsimonious four region model provide a better base for analysis than other regional alignment of states? All of these questions point to the need for further, future study given what was revealed in this study's findings.

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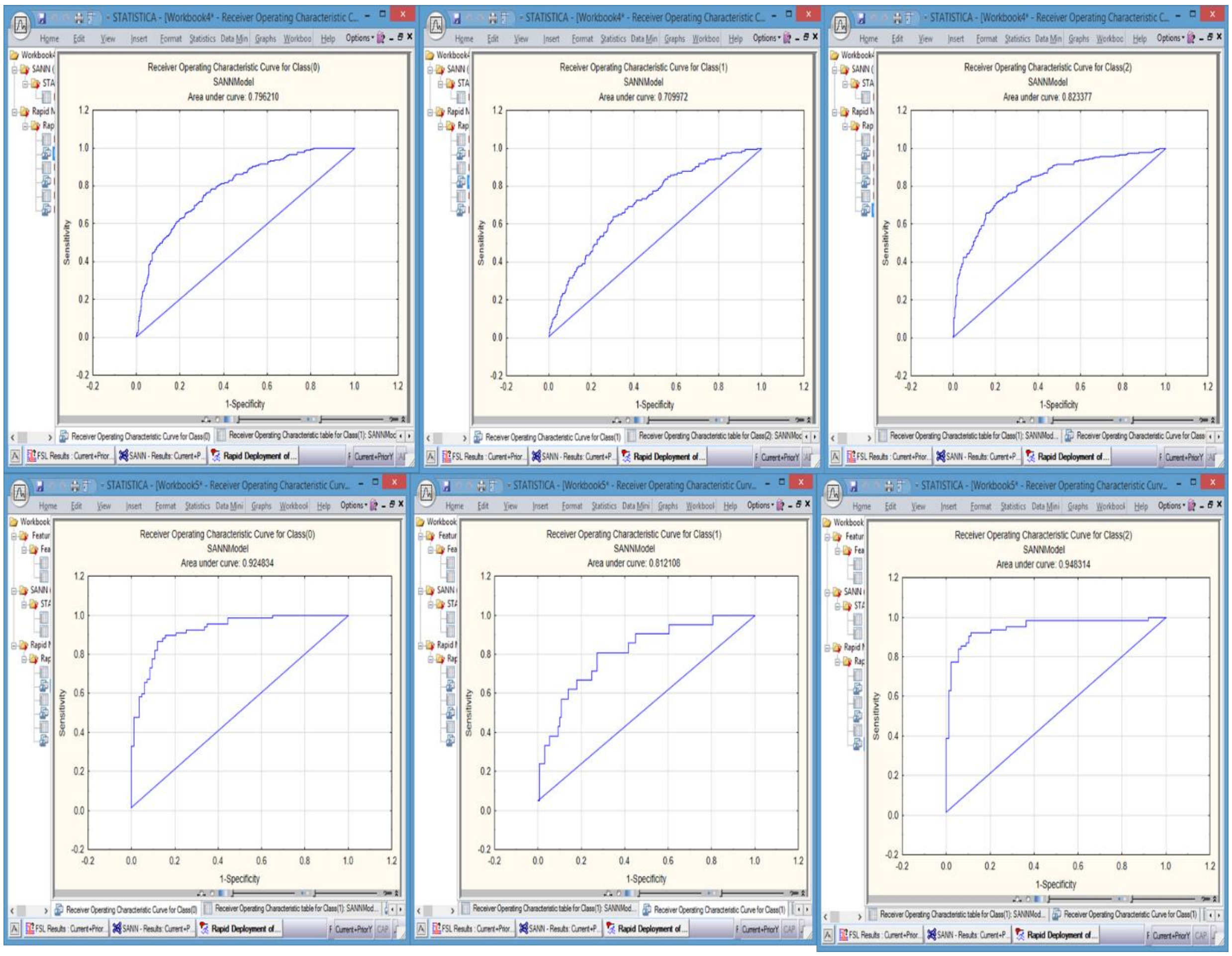
APPENDIX A: FULL LIST OF VARIABLES

Abbreviation	Full description	Level
StateYear	Unique identifier: each state for each year of the study (e.g. California 2001)	State
Agriculture	Percentage of State GDP Output generateg from agricultural related activities	State
Munafacturing	Percentage of State GDP Output generateg from Industrial/munafacturing related activities	
Services	Percentage of State GDP Output generateg from services	
Count-sqMi	Number of disasters per square mile	State
Count-pop	Number of disasters per 100,000 persons residents	
Affected	Percentage of counties affected that year	
Duration	Sum of ((counties affected) * (number of days)) /(no of counties in the state)	
Damages	Damages / State-GDP	
Injuries	Injuries / State Population	
Deaths	Deaths / State Population	
MWCouAffected	(Number of Midwest counties affected) / (number of counties in the midwest)	Regional Aggrergrate
MWDamages	(Damages in the midwest) / (GDP for midwest region)	
NECouAffected	(Number of northeast counties affected) / (number of counties in the northeast)	
NEDamages	(Damages in the northeast) / (GDP for northeast region)	
SouCouAffected	(Number of South counties affected) / (number of counties in the south)	
SouDamages	(Damages in the south) / (GDP for midwest south)	
WestCouAffected	(Number of West counties affected) / (number of counties in the west)	
WestDamages	(Damages in the west) / (GDP for west region)	
PriCount-sqMi	Prior Year's Count-sqMi	State
PriCount-pop	Prior Year's Count-pop	
PriAffected	Prior Year's Affected Normailzed	
PriDuration	Prior Year's Duration Normailzed	
PriDamages	Prior Year's Damages Normailzed	
PriInjur	Prior Year's Injur Normailzed	
PriDeaths	Prior Year's Deaths Normailzed	
PriMWCouAffecte	Prior Year's MWCouAffected	Regional Aggrergrate
PriMWDamages	Prior Year's MWDamages	
PriNECouAffected	Prior Year's NECouAffected	
PriNEDamages	Prior Year's NEDamages	
PriSouCouAffected	Prior Year's SouCouAffected	
PriSouDamages	Prior Year's SouDamages	
PriWestCouAffect	Prior Year's WestCouAffected	
PriWestDamages	Prior Year's WestDamages	
RealGDP	Real GDP (year = 2000)	State
5YRavge	5 year moving average of GDP (does not include present year)	State
gdp-Diff	Difference between real GDP and the 5 year average.	State
Class	0 = large negative deviation, 1 = very little ir no deviation; 2 = large positive deviation	State

APPENDIX B: THE ROC CURVES



Top row presents output for the 50-state national model (across the page: 0, 1, and 2 states).

Bottom row presents the output for the northeast model (across the page: 0, 1, and 2 states).

APPENDIX C: SUMMARY OF DISASTER COUNTS AND DAMAGES IN 2000 DOLLARS

Disaster Types	Count of HAZARD_TYPE	Damages '2000 Dollars'
Avalanche	484	$ 2,914,371
Coastal - Flooding	6,265	57,834,590,643
Drought - Heat	124	314,896,623
Earthquake	24	25,652,144,847
Flooding	34,401	46,887,677,145
Fog	440	20,432,210
Hail	20,506	12,226,215,825
Heat	4,318	996,832,344
Hurricane/Tropical Storm	2,770	126,960,092,349
Landslide	403	1,474,429,371
Lightning - Severe Storm/Thunder Storm	90,504	18,399,552,081
Tornado	11,631	13,720,636,780
Tsunami/Seiche	15	25,125,060
Volcano	1	-
Wildfire	1,292	11,479,314,935
Wind	30,071	6,001,242,341
Winter Weather	39,382	11,852,006,094
Grand Total	242,631	$ 333,848,103,019

Counts are reported at the county level. This translates to 57,733 when analysis at state level incidents per year.

APPENDIX D: 4 REGIONAL ALIGNMENT OF US STATES

Northeast	South	Midwest	West
Connecticut	Alabama	Kansas	Alaska
Maine	Arkansas	Illinois	Arizona
Massachusetts	Delaware	Indiana	Colorado
New Hampshire	Florida	Iowa	California
New Jersey	Georgia	Michigan	Hawaii
New York	Kentucky	Minnesota	Idaho
Pennsylvania	Louisiana	Missouri	Montana
Rhode Island	Maryland	Nebraska	Nevada
Vermont	Mississippi	North Dakota	New Mexico
	North Carolina	Ohio	Oregon
	Oklahoma	South Dakota	Utah
	South Carolina	Wisconsin	Washington
	Tennessee		Wyoming
	Texas		
	Virginia		
	West Virginia		
n=9	n=16	n=12	n=13