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Flooding and the Midwest economy: assessing the Midwest floods of 1993 and 2008

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Abstract This paper examines local economic vulnerability over time by comparing how county-level unemployment rates were affected by two major flooding events in the Midwest region, one in 1993 and the other in 2008. One of the challenges for studies of this kind is to separate out the impact of the hazard events from the effects of more general macroeconomic dynamics. A case–control design is used in the analysis for that purpose, applying an optimal matching algorithm to select a non-flooded control county for each flooded case county and then model the flood effects using ARIMA intervention models. The main research finding of this study is that the 1993 flood affected a larger area and caused more severe economic disturbances than the 2008 flood. Counties that were hit hard in 1993 seemed to fare well in 2008. It was also found that higher damage was associated with an increase in the county-level unemployment rate.

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Introduction

The documentation of the economic impacts of unexpected events such as earthquakes, floods, tsunamis and other climatic activities has not been a prominent feature of the economic analysis literature. In large part, this stems from the fact that most models operate under equilibrium conditions and rely on long series of data for calibration and estimation. Unexpected events present researchers with a problem that they are unique, relatively unpredictable (especially in terms of timing) and data collected about the event is often less precise and consistent with common standards.

Notwithstanding these problems, several attempts have been made in the recent past to advance the state of the art. This line of research includes impact assessment based on an input–output (IO) framework and social accounting matrices (SAM) (such as, Cole 1995, 1998). Methods used include sequential interindustry modeling (Okuyama et al. 2001), computable general equilibrium (CGE) models (Seung et al. 2000; Rose and Liao 2005; Rose et al. 2007), and regional econometric modeling (Ellson et al. 1984; Guimaraes et al. 1993; Chang and Falit-Baiamonte 2002). A notable source is the collected work of Okuyama and Chang (2004) that provided in one volume a collection of a diverse set of approaches to this problem. Researchers have been struggling with issues of the appropriate spatial definition (e.g. community, county, state), the appropriate time period (days, month, quarter etc.) and other myriad problems of differentiating the negative effects from the positive stimuli associated with recovery investments.

Floods, as one important form of natural hazard in the United States, occur in very specific geographic spaces that most often cut across jurisdictional boundaries, state lines and other human-generated subdivisions of reality. While river basins are recognized as important features in hydrographic and environmental research, they are rarely embraced as meaningful economic units. Accordingly, socio-economic data have often to be manipulated to “fit” the geographic “contours” of flooded areas or a compromise adopted whereby aggregations of counties are considered. The issue becomes more difficult when the percentage of a county that is impacted by a flood is much larger or smaller than adjacent counties; the aggregation of counties into a “flooded region” for assessment can thus overlook important spatial variations within these regions. The issue, unfortunately, is endemic in any spatial analysis. At the state level, the problem is even more severe and thus analysis conducted at this level may significantly overstate or understate the impacts that occur in specific counties. In this paper, the focus will be at the county level since this appears to be the most geographically relevant unit and the time frame adopted will be monthly. The choices stem in large part from data availability and the constraints imposed by decision-making units.

A second issue is that floods occur during different stages in the economic development of an economy and at different points in the business cycle; further, long-term structural changes can exacerbate or mitigate the impacts of floods. This economic context is important since any estimated job losses associated with the 2008 flood are likely to be dwarfed by the magnitude of the economic declines associated with the recession. That said, it is still important to assess the economic impacts of the flood; while unexpected—in terms of time and less so in terms of space—the probability of another flood event in many of the same locations is high. This probability is likely to increase if forecasted patterns of long-term climate change increase the incidence of major summer storms in the Midwest over the coming decades.

The set of empirical studies that have assessed the impacts of natural hazards is extensive; however, comparative studies of local economic responses to repetitive hazardous events are scarce. Much of the existing research takes a case study approach: one or multiple municipalities are studied but only for a single disaster event (such as, Kroll et al. 1991; Chang and Falit-Baiamonte 2002; Webb et al. 2002; Ewing et al. 2005). Only a few studies have monitored places over time to study the impacts of repetitive hazards (i.e., Belasen and Polachek 2008). Comparative studies can be very informative; they enhance the understanding of regional responses to hazards over time, and thus provide information for modeling spatial economic impacts of repetitive disasters.

In this paper, the focus will be on the analysis of the economic impacts of two costly regional floods in the Midwest, one in 1993 and the other in 2008. The spatial patterns of the two Midwest floods will be compared and an examination will be made to explore whether the flood shocks had any significant effects on county-level unemployment rates.

As noted earlier, one of the challenges for studies of this kind is to separate out the impacts of hazard events from macroeconomic dynamics. A quasi-experimental case–control design is adopted for this purpose. An optimal matching algorithm is applied to select the best-matching non-flooded control counties for flooded case counties and then autoregressive integrated moving average (ARIMA) models are used to analyze effects of the two floods.

The rest of the paper is organized as follows: “Background of 1993 and 2008 Midwest floods” discusses the extent of the 1993 and 2008 floods as background for this study. “Research design” lays out the research design. “Data” presents data sources while “Results” displays results from the case–control matching design and time-series analysis. “Discussions and conclusions” discusses findings and offers some conclusions.

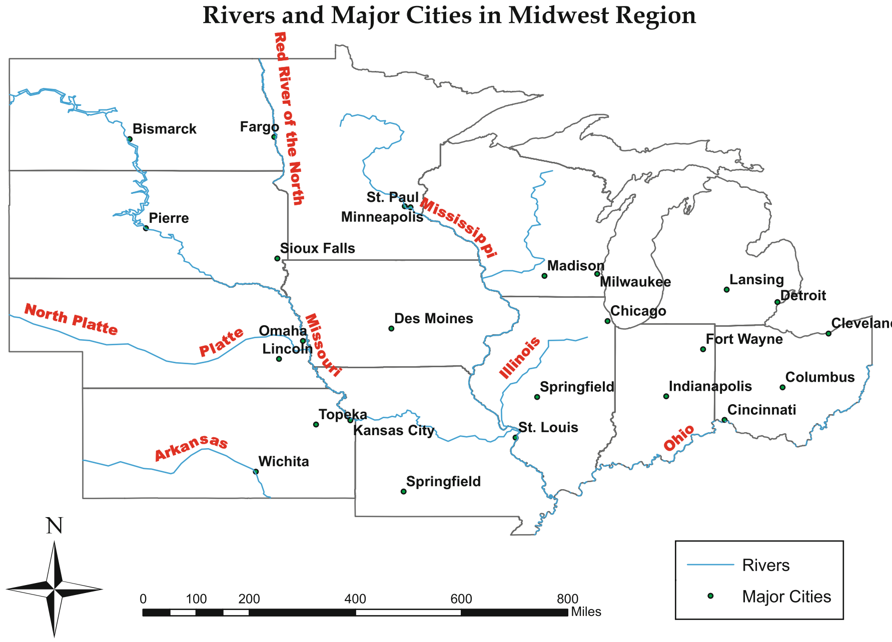

Fig. 1 Rivers and major cities in midwest region

Background of 1993 and 2008 Midwest floods

The 1993 Midwest flood turned out to be the most costly riverine flooding event during the 20th century in the United States (Perry 2000). It started with a wet winter in 1992, followed by extensive rainfall and flooding in the spring of 1993. When the summer came, more rainfall in July and August caused major flooding in the Midwest region. (For rivers and major cities in Midwest region, see Fig. 1) The upper Mississippi River and its tributaries swelled. Levies were breached at multiple points and nine Midwestern states (Illinois, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota and Wisconsin) were affected by flooding and 519 counties were declared as presidential disaster areas.[1]

Fifteen years later, in the summer of 2008, the Midwest again experienced large-scale regional flooding caused by extensive rainfall. A total of 358 counties in ten Midwestern states (Illinois, Indiana, Iowa, Kansas, Minnesota, Missouri, Nebraska, Ohio, South Dakota and Wisconsin) were declared as presidential disaster areas. Some of the presidential disaster areas in 2008 overlapped with those in 1993. Table 1 shows the number of counties affected by the two floods. According to FEMA, about half of the declared counties in 1993 were declared again in 2008 for flood-related emergencies. The overlap in impact areas of the two floods provides the opportunity to study the effect of past flood experience on damage and responses in a later event.

Table 1 Counties affected by the floods of 1993 and 2008

	N
Declared in the 1993 flood	519
Declared in the 2008 flood	358
Declared in both floods	234

Data Source: FEMA

One difficulty encountered in this comparative study lies in the fact that disaster damage was not consistently documented and reported by one single source. Hence, it is necessary to pool data from two different sources and to adopt some strategy to ensure compatibility. The 1993 flood damage data were retrieved from the U.S. Army Corps of Engineers, covering seven detailed damage categories including residential, commercial/industrial, public facilities, transportation, utilities, agriculture, and emergency services. However, no exact dollar value was reported

[1] The *Robert T. Stafford Disaster Relief and Emergency Assistance Act* authorizes the President to issue major disaster declarations to areas that were overwhelmed by disasters. Presidential disaster declaration triggers federal funding for disaster assistance.

for all these categories. Instead, damage was reported in discrete categories, i.e., less than $500,000, $500,001–$999,999, etc. The 2008 flood damage data were retrieved from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), maintained by the Hazards & Vulnerability Research Institute at the University of South Carolina (Hazards and Vulnerability Research Institute 2009). In SHELDUS, damage was reported for only two categories, property damage and crop damage. Agricultural loss in the 1993 flood is compared with crop damage in the 2008 flood; also examined is the residential loss in 1993 versus the property damage in 2008.

Overall, the flood in 1993 caused more widespread damage than the one in 2008 (see Figs. 2 and 3). The 1993 flood struck a fairly contiguous area at the core of the Midwest region. Almost the entire state of Iowa, two-thirds of Missouri and Wisconsin, half of North Dakota, South Dakota, and Minnesota, and many counties in Illinois, Kansas and Nebraska suffered from residential and agricultural damage as a result of the 1993 flood. In contrast, although two more states were declared as Presidential major disaster areas, the impact area of the 2008 flood was smaller than that for the 1993 flood. Iowa, Wisconsin, Indiana, and Ohio experienced most of the property and crop damage. Michigan was not affected in the 1993 flood, but suffered from flood damage in 2008. The other states had some degree of damage but much less than that caused by the 1993 flood.

Although there is some overlap, the geographic areas stricken by the 1993 and 2008 Midwest floods were different. High agricultural damage in 1993 was observed at the center of the Midwest region, approximately in northern Iowa, southern Minnesota and east South Dakota, and in areas along the Missouri River in Missouri and the northeast of Kansas. The counties that suffered high residential damage were located along the Mississippi River (especially along the Illinois-Iowa and Illinois-Missouri borders) and along the Missouri River in the state of Missouri. In contrast, in 2008, the highly damaged areas, measured both by property and crop damage, exhibited a bi-polar pattern. One high-damage pole was in Iowa and southern Wisconsin, the other in Indiana and eastern Illinois. The bi-polar damage pattern coincided with an above average precipitation pattern during the summer of 2008.

Research design

A quasi-experimental design was adopted to analyze the flood impacts. First, best matching non-flooded control counties are selected as a basis against which counties that were flooded could be compared. Then, ARIMA intervention models were used to estimate the extent of the shocks on county-level unemployment rates in the two flooding periods.

Case–control design

Case–control design is an often-used approach in impact assessment. Rather than interpreting causal effects based solely on observed outcomes in a treated group (or case group), an untreated control group is used as reference of potential outcomes. Treatment effects are then interpreted from case–control differences (Imbens and Wooldridge 2009). Case–control designs have been applied in social science for policy evaluations (i.e., Spiegelman and Woodbury 1990; Card 1992; Card and Krueger 1994; Isserman and Rephann 1995). Only very recently was this design used to evaluate economic impact of natural hazards (such as, Xiao 2008, 2011).

Within the case–control design framework, a widely studied approach is matching that relies on selecting the closest controls for a treatment group based on some pre-set baseline measurements. In this study, the goal is to examine the economic impacts of two floods. Therefore, the baseline measurements should include variables that influence the economic prospects of a locality. Table 2 lists the socioeconomic variables used in the matching. For instance, urban hierarchy measures the locus of a county in the constellation of cities of various sizes. Aggregate accessibility is measured by population potentials (the total number of people) in a radius of 60 miles from the centroid of a county and in a 60–500 mile ring area. Income and industrial structure is measured by the earnings structure of a county, including percentages of income from farming, manufacturing, service, government and government enterprises, proprietors, dividends, interest, and rent, and residence adjustment. The percent of population age 25 or older with at least high school degree is treated as a proxy for the quality of human capital. Prosperity measures include the poverty rate, per capita income,

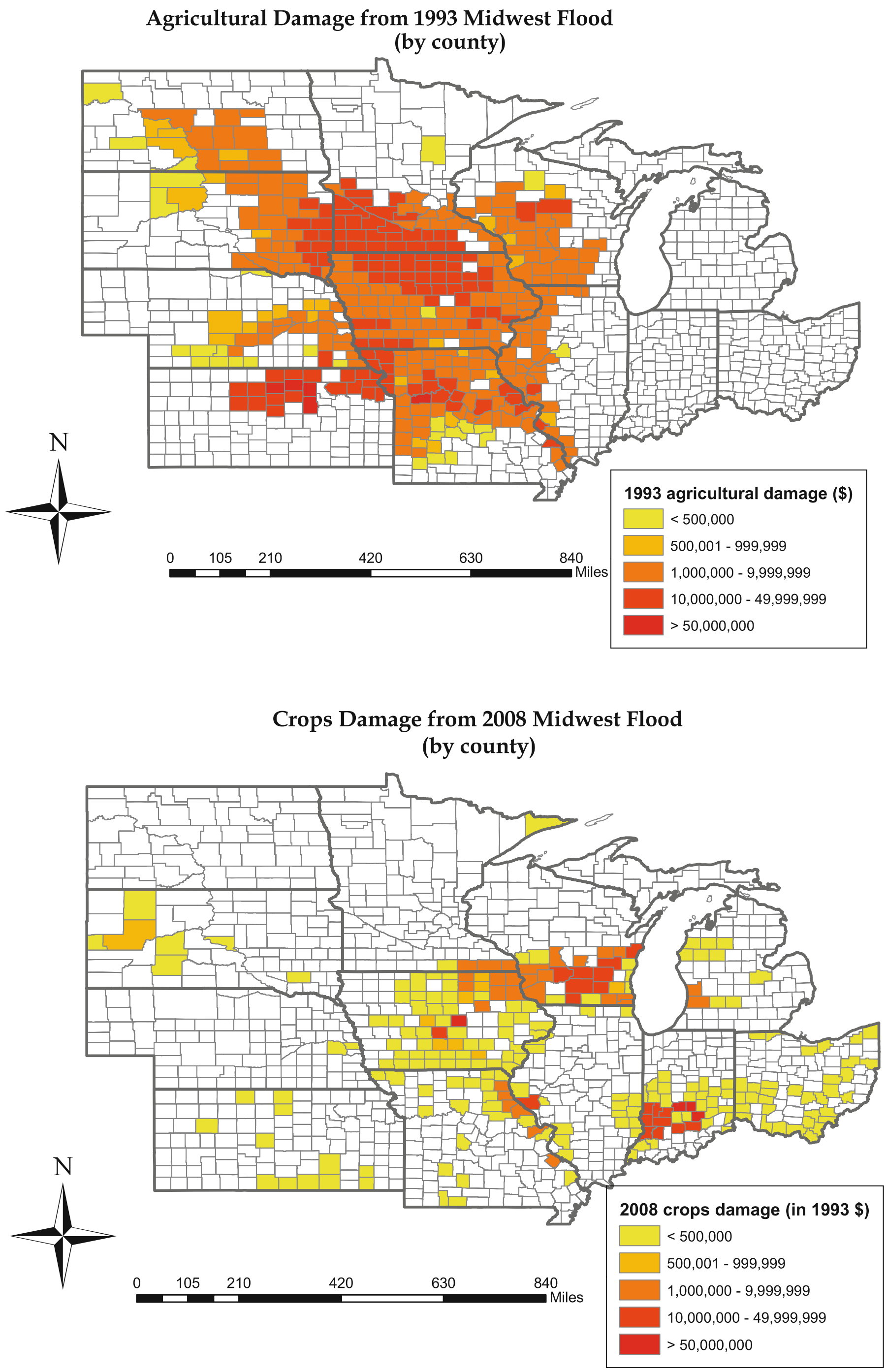

Fig. 2 1993 agricultural damage vs. 2008 crops damage

and the unemployment rate. Past population and total income growth trends are also considered in the matching. To capture industrial structural change, changes in the share of manufacturing income and service income are also included in the set of socioeconomic variables. We also consider county size measured by land area and population, and the rate of in- and out-migration (see Table 2).

Geographic location and topography matter in flood hazards. Outbreaks of riverine flooding usually

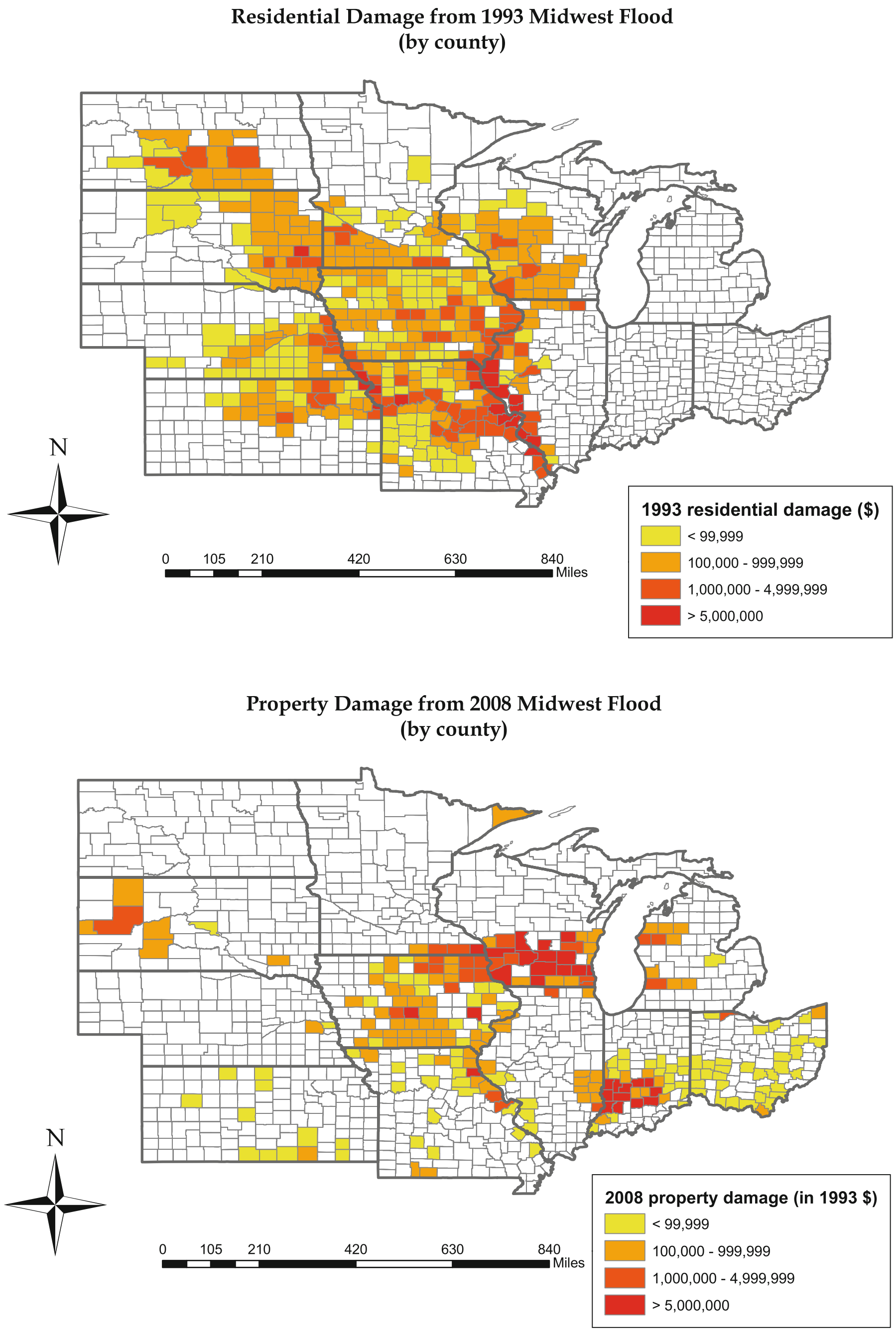

Fig. 3 Residential damage in 1993 vs. property damage in 2008

start from the river channel; lower elevations are associated with higher probabilities of flooding. Therefore, also included in the matching measurements is the shortest distance to a major river, which serves as a proxy to account for potential of riverine flooding and subsequent flood damage.

To complete the matching process, a pool of candidate control counties is identified. In this study,

Table 2 Variables used in case–control match

Urban hierarchy (Census)	Income and industrial structure (BEA)
Distance from an urban area with 50,000- 100,000 people, 1990	Pct. of residence adjustment, 1989
Distance from an urban area with 100,000- 250,000 people, 1990	Pct. of farming income, 1989
Distance from an urban area with 250,000- 500,000 people, 1990	Pct. of manufacturing income, 1989
Distance from an urban area with 500,000- 1,000,000 people, 1990	Pct. of service income, 1989
Distance from an urban area with more than 1,000,000 people, 1990	Pct of income from gov. and gov. enterprises, 1989
	Pct. of proprietor income, 1989
	Pct. of dividends, interest, and rent, 1989
Market potential (Census)	
Log of the sum of population within 60 miles, 1990	
Log of the sum of population within 60–500 miles, 1990	Economic structural change (BEA)
	Change in share of manufacturing income, 1985–1989
Prosperity	Change in share of service income, 1985–1989
Poverty rate, 1990 (Census)	
Per capita income,1989 (BEA)	Size
Unemployment rate, 1990 (Census)	Land area, 1990 (Census)
	Log of population, 1989 (BEA)
Population and income growth trend (BEA)	
Population growth rate, 1985–1989	Human capital (Census)
Total income growth rate, 1985–1989	Pct. of population 25 + with at least high school degree, 1990
Migration pattern (IRS)	
In and out migrating population as a percentage of total population, 1989	Geographic location (ESRI)
	Shortest distance to a major river

Data sources are listed in (). *Census* U.S. Census Bureau, *BEA*, U.S. Bureau of Economic Analysis, *IRS*, U.S. Internal Revenue Service, *ESRI* Environmental Systems Research Institute, Inc

candidate control counties are those (1) that were not declared as presidential disaster areas; (2) that did not suffer any residential/property damage in either flood and (3) that were not within 30 miles of a declared county or a county with residential/property damage. The purpose of imposing a 30-mile spatial caliper is to control for spatial spillover effects, the influence of a flooded county on its neighboring counties. Then, the Mahalanobis distance between each case county and candidate control county is calculated. The Mahalanobis distance is defined as:

$$d(X_T, X_i) = (X_T - X_i)' R^{-1} (X_T - X_i) \quad (1)$$

Where X_T is a vector of measures (as specified in Table 2) of a case county and X_i is that of a candidate control county. R is the variance–covariance matrix associated with the variables in X. A smaller Mahalanobis distance indicates a higher degree of similarity for a given pair of counties.

Finally, the best-matching control counties for the case counties are identified. The county pairs that minimize the group sum of Mahalanobis distances are considered to be the best match.

ARIMA intervention models

Given the dearth of data at the county level, an analyst is often restricted to consideration of a limited functional form. ARIMA models thus offer a parsimonious way to exploit relatively limited data but for which an extensive time series is available. An unexpected event can thus be handled through the inclusion of a dummy variable to account for a disruption in the time series. The intervention analysis tests for significant changes in a time series based upon the null hypothesis that the interventions (i.e., the 1993 and 2008 floods) caused no change to the time series. Intervention analysis was used in other disaster impact studies such as Hewings et al. (2000) and Ewing et al. (2005). The major methodological difference between this study and those earlier studies lies in the fact that a quasi-experimental matching design is used to select a local control group for the treatment group. The control group accounts for fluctuations in the macro economy that could be easily mingled with the true impacts from flood events, i.e., due to proximity in time of an economic recession and a flood event.

In this paper, an ARIMA model with case–control design to better estimate the flood effects. According to Box et al. (1994), the basic ARIMA model takes the following form:

$$\phi(B)\nabla^d z_t = \theta(B)a_t, \tag{2}$$

where z_t is the variable of study, in this case, the mean of unemployment rate of the case group at time t. The moving average MA(q) component is defined as

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q,$$

and the autoregressive AR(p) element is defined as

$$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p,$$

where B is a time lag operator and … a_{t-1}, a_t, a_{t+1}, … is a sequence of white noise, $\nabla = 1 - B$, and d represents the differencing necessary to make the noise series stationary. Seasonality can be written as

$$\Phi(B^s)\nabla_s^D z_t = \Theta(B^s)a_t, \tag{3}$$

where $\Phi(B^s)$ and $\Theta(B^s)$are polynomials representing the MA and AR processes, respectively for the seasonal cycle, s = 12, and $\nabla_s = 1 - B^s$. Substituting (2) into (3), we get a multiplicative ARIMA process with consideration for seasonality:

$$\phi(B)\Phi(B^s)\nabla^d\nabla_s^D z_t = \theta(B)\Theta(B^s)a_t \tag{4}$$

We then add to Eq. 4 a variable that represent the mean of the unemployment rate of the control group at time t (*UnempR_cl$_t$*), and two dummy variables ($P_{1993}^{(T)}$ and $P_{2008}^{(T)}$) that specify the impact periods of the 1993 and 2008 floods, which are defined as:

$$P_{1993}^{(T)} = \left\{ \begin{array}{r} 1, t = \text{July or August, 1993} \\ 0, \text{otherwise} \end{array} \right\}, \text{ and}$$

$$P_{2008}^{(T)} = \left\{ \begin{array}{r} 1, t = \text{June or July, 2008} \\ 0, \text{otherwise} \end{array} \right\}.$$

We follow the model fitting procedures described in Box et al. (1994) and use the proc ARIMA procedure in the SAS program to estimate the final model.

Data

The choice of economic variable for analysis is constrained by data availability. Many variables that are frequently used to measure performance of an economy, i.e., gross product, income per capita, etc., are not available on a fine regional scale in a timely manner. Hence, we use the unemployment rate to represent local economic activities because business interruption and job losses are reflected in this variable and the time series is publicly available at the county level on a monthly basis from the U.S. Bureau of Labor Statistics (BLS). The data time span is from January 1990 to February 2009, a total of 230 months. Data on variables used in case–control matching are from the U.S. Census, U.S. Bureau of Economic Analysis, Internal Revenue Services, and Environmental Systems Research Institute, Inc. (ESRI) (see Table 2 for details).

The study area includes Midwestern counties that suffered from residential/property damage in both 1993 and 2008 floods. As discussed earlier, the flood damage data are pooled from two different sources, the U.S. Army Corps of Engineers and SHELDUS. The severity of damage from flooding on local economy is proxied by residential damage in 1993 flood and property damage in 2008 flood. We define low damage as \$1–\$999,999, middle damage as \$1,000,000–\$4,999,999, and high damage as more than \$5,000,000. In 1993, a total of 333 counties fell into the low damage category, 69 into the middle damage category, and 22 into the high damage category.

Counties are thus grouped into 5 categories by damage levels in the 1993 and 2008 floods: the first category (namely Case 1) includes counties that experienced zero damage from the 1993 flood but suffered at least some property damage in the 2008 flood. The second, third, and forth category (Cases 2, 3, and 4) consist of counties with, respectively, low, middle and high damage in 1993. The fifth category

(Case 5) is composed of counties that reported extremely severe property damage (>$50 million in 1993 dollars) in 2008.

Results

Comparison of flood damage in 1993 and 2008

Table 3 presents summary statistics of county-level flood damages in 1993 and 2008. The consumer price index of the Midwest region reported by the BLS is used to adjust for inflation; all 2008 values are deflated to 1993 dollars. The 2008 flood caused property losses in 140 counties that were outside of the 1993 flood impact area (Case 1). On average, these counties had about $2.0 million dollars (in constant 1993 dollars) in property damage as results of the 2008 Midwest flood.

Compared to the counties in Case 1, those reporting residential damage in 1993 turned out to suffer low property damage in 2008 and the extent of the damage was very similar for the low (Case 2), middle (Case 3), and high damage (Case 4) county groups. The average property damage as a result of the 2008 flood was $329,087, $395,771, and $414,199 (in constant 1993 dollars), respectively, for the low, middle and high damage groups in the 1993 flood. The variations in the extent of property damage for these three county groups were also very close (the standard deviations range between 1.1 million and 1.9 million).

There were eight counties that had more than $50 million (in constant 1993 dollars) in property damage as a result of the 2008 flood. The highest property damage was observed in Linn County, Iowa, which lost as much as $5.1 billion (in constant 1993 dollars) to the 2008 flood; followed by Green County, Wisconsin, which lost more than $899 million (in constant 1993 dollars). It should be noted that these counties had relatively low damage in 1993. Half of eight counties reported no damage in 1993. Only two counties reported less than $1 million in residential damage and the remaining two counties had residential damage between $1 million and $5 million.

Unemployment impacts of the two floods

The damage estimates provide just one indicator of the impact of the floods; of equal concern, is the impact on the economy, especially looking ahead several months after the floods. Therefore, we compare the unemployment rate time series of the case and control groups for further insights.

The matching algorithm described in "Case–control design" generated fairly good case–control matches. Of all possible case–control pairs, the average Mahalanobis distance is 32.0 with the maximum at 447.0 and the minimum at 2.5. The mean group Mahalanobis distances for cases 1–5 ranged between 6.3 and 12.0, much smaller than the average Mahalanobis distance of all possible case–control pairs (see Table 4 for details). The larger the sample size, the larger the overall Mahalanobis distance, i.e., the Mahalanobis distance for case 5 (8 observations) is 6.3, compared to 12.0 for case 2 (333 observations). This occurs when more case counties need to be paired up with control counties, and inferior matches have to be selected.

Figure 4 shows the case–control unemployment rate comparisons for cases 1–5. Obvious spikes of high case–control differences in unemployment rate were observed in cases 3 and 4, the middle and high damage groups in the 1993 Midwest flood. The case–control differences in unemployment rate of cases 1

Table 3 Flood damage in 1993 and 2008

	Residential damage in 1993 (in 1993 dollars)				Case 5
	Case 1 No damage ($0)	Case 2 Low damage ($1–$999,999)	Case 3 Middle damage ($1,000,000–$4,999,999)	Case 4 High damage (>=$5 million)	Extremely high damage in 2008 (> $50 million in 1993 dollars)
N	140	333	69	22	8
Average property damage in 2008 (in constant 1993 dollars)	2,004,880	329,087	395,771	414,199	822,349,940
SD	6,641,463	1,361,213	1,925,692	1,096,295	1,756,808,409

Table 4 Average group Mahalanobis distance

	Case 1 No damage, 1993	Case 2 Low damage, 1993	Case 3 Middle damage, 1993	Case 4 High damage, 1993	Case 5 Extremely high damage, 2008
Mean	9.8	12.0	9.3	7.9	6.3
SD	13.8	5.1	4.2	1.7	1.7

and 5 seemed to drop slightly during the 1993 Midwest flood.

The 2008 flood did not seem to be associated with sharp changes in case–control unemployment rate differences. Unemployment rates of both the cases and controls rose sharply in the fall of 2008 as a result of the housing market melt down. However, the case counties of cases 2, 3, and 5 saw relatively smaller increases in unemployment rates compared to their control counties.

Table 5 presents results from ARIMA intervention models. In 1993, the changes in unemployment rates reflected the levels of residential losses. Higher flood damage was associated with higher levels of unemployment rate increases. The unemployment rate of the counties that had no reported damage in 1993

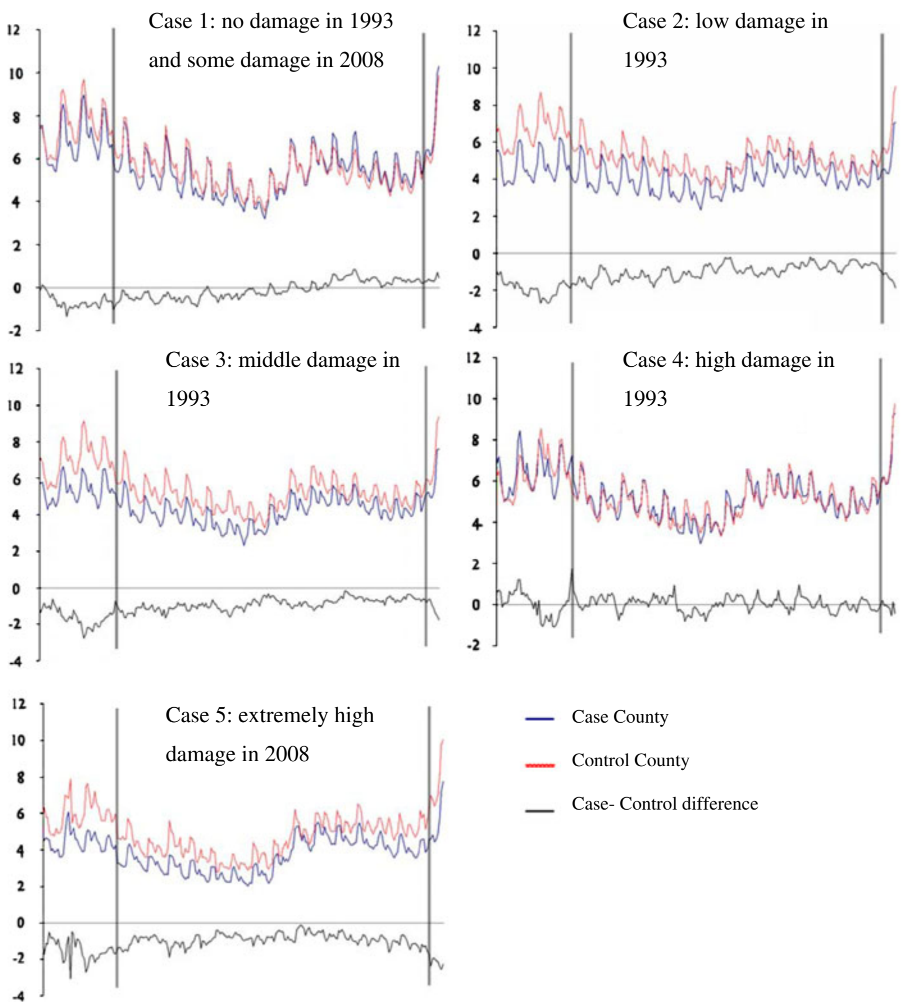

Fig. 4 Case –control comparison of unemployment rate

(Case 1) was 0.23 percentage points lower than their control counties and the decrease is statistically significantly. This indicates possible improvements in labor market conditions in the Midwestern counties that did not have residential losses in 1993. The coefficient of the 1993 flood intervention variable of the low damage group (Case 2) is also negative (−0.03) but not statistically significant, reflecting negligible changes in the unemployment rate in these counties during the 1993 flood. Positive and significant coefficients on the 1993 flood intervention variables are observed in the middle and high damage groups (Cases 3 and 4). During the flood in 1993, the unemployment rate of the middle damage group rose by 0.18 percentage points and that of the high damage group by a significant 0.77 percentage points.

The 2008 flood did not seem to cause any significant changes in the unemployment rate. For Cases 1–4, the coefficients on the 2008 flood intervention variable are close to zero (between −0.06 and 0.06), much lower in absolute value than those estimates for the 1993 flood intervention variables. Furthermore, these coefficients are not statistically significant.

To further examine unemployment impacts of the 2008 flood, the counties that experienced extremely severe property damage (Case 5) as a result of the 2008 flood were studied separately. Regression results show that these counties' unemployment rate was 0.23 percentage points lower than their control counties in 1993 and it is statistically significant. Therefore, improvements in labor markets were observed in 1993. This result is consistent with an earlier observation that the extremely high damage counties in 2008 actually suffered relatively low damage in 1993 (as discussed in "Comparison of flood damage in 1993 and 2008"). Interestingly, the coefficient on the 2008 flood intervention variable is close to zero and insignificant, indicating no significant change in the unemployment rate during the 2008 flood event in the counties that reported very high property damage. To sum up, the impacts from the 2008 flood were much less severe than those experienced in 1993.

Discussions and conclusions

Natural disasters, as shocks, often cause disturbances in socioeconomic systems. One of the least understood areas in social science is how local economies respond to these external shocks. Our study contributes to filling this void by examining economic vulnerability over time at the county-level. Vulnerability, as a central concept to the climate change studies, has been defined in many ways by different research traditions (Gallopin 2006). One of the most well cited definitions is from the Intergovernmental Panel on Climate Change (IPCC), by which vulnerability is defined as "the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes," and vulnerability is assessed as a function of hazard exposure, the system's sensitivity, and its adaptive capacity (see Annex II, Glossary of Terms in IPCC 2007). Following this definition, we discuss our findings from the comparative study of the 1993 and 2008 Midwest floods.

Table 5 ARIMA model summaries (economic variable: unemployment rate)

Parameter	Case 1 No damage, 1993 Estimate	Case 2 Low damage, 1993 Estimate	Case 3 Middle damage, 1993 Estimate	Case 4 High damage, 1993 Estimate	Case 5 Extremely high damage, 2008 Estimate
MA(12)	0.718 ***	0.770 ***	0.728 ***	0.660 ***	0.901 ***
AR(1)	0.917 ***	0.928 ***	0.907 ***	0.825 ***	0.981 ***
AR(12) seasonal	0.964 ***	0.994 ***	0.973 ***	0.888 ***	0.998 ***
UnempR_cl	0.941 ***	0.684 ***	0.726 ***	0.939 ***	0.226 ***
Flood_93	−0.232 ***	−0.034	0.179 **	0.770 ***	−0.233 *
Flood 08	0.013	0.015	−0.055	0.057	−0.065

*** Significant at 0.01 level, ** Significant at 0.05 level, * Significant at 0.1 level

Overall, the results suggest that the counties in the Midwest region were more vulnerable in the 1993 flood than the 2008 flood. The Midwest floods struck different areas in 1993 and 2008 albeit with some overlap. The 1993 flood, compared to the one in 2008, affected more counties (indicating higher level of *hazard exposure* in 1993) and caused more economic disturbances (indicating higher *vulnerability* in 1993). The changes in the unemployment rates associated with the 1993 flood tend to be significant. In contrast, the changes associated with the 2008 flood are insignificant, even in counties with extremely severe flood damage (indicating less *sensitivity* in 2008).

Counties that were extremely vulnerable in 1993 appeared to be more resilient in the 2008 flood. The counties that were hit hard in 1993, in general, fared better in 2008, indicated by less hazard exposure and less vulnerable outcomes. The high damage counties (>$5 million in residential damage) in 1993 saw only slight property damage in 2008 (less than half of a million dollars). On the other hand, in 2008, extremely high property damage occurred in counties that had only low or no residential damage in 1993. None of the counties with over $50 million (in constant 1993 dollars) in property damage in 2008 reported residential damage higher than $5 million in 1993. This phenomenon may be caused by the spatial differences in the quantity of rainfall and flooding in 1993 and 2008. It could also be due to the improved adaptive capacity in those hard-hit counties after the 1993 event. The post-flood mitigation, such as property buyouts and levy reinforcements, in the flood-impaired counties may have reduced the propensity of hazard exposure of these counties to future flooding. Businesses may have learned from the 1993 flood experience how to strategically cope with future flooding.

Economic vulnerability is found to be conditioned on the severity of the exogenous shock. Counties can withstand some degree of exogenous disaster shock without significant changes in the unemployment rate. However, as physical damage increases, the impact on county-level labor market becomes negative and significant. The 1993 flood, as the most costly flood of the twentieth century in the United States, caused notable labor market interruptions. The local labor markets of counties that suffered no damage were better off during the flood, indicated by lower than usual unemployment rate. The flood did not seem to affect the unemployment rate in counties that had low flood damage. The counties that had middle and high damage, however, seemed to experience increased unemployment rates during the flood. The more damage a county suffered, the higher the negative impact on its local labor market. There might have been shifts in employment opportunities from the heavily damaged areas to relatively low damage areas.

It is also important to note that economic vulnerability is likely to be conditioned by the geographic scale of analysis. We use the county as the unit of analysis because it is the smallest geographic unit for which economic time series data are consistently reported. However, we do acknowledge heterogeneity in flood exposure within a single county. Localities may be found to be more vulnerable in sub-county analysis.

To reduce local economic vulnerability to natural disaster, policies should be designed and applied toward reducing hazard exposure, decreasing sensitivity of the economic system, and enhancing the system's adaptive capacity. To reduce hazard exposure, communities could adopt structural mitigation strategies (such as constructing and maintaining levees and dikes), and more importantly, non-structural mitigation measures (for instance, apply land use planning to curb development in hazard-prone areas) to reduce the probability of flooding in communities. To decrease sensitivity of the economic system, communities should enhance weather forecasting and warning to facilitate hazard preparedness. Also, certain types of businesses, such as those in the manufacturing and some service sectors, and those that are large were found to be less vulnerable to natural disasters (Tierney 2006). Attracting and increasing the proportion of such businesses in the local industrial mix will reduce the location's economic sensitivity to hazards; this option may be difficult to pursue in an era of economic retrenchment Finally, to enhance the local economy's adaptive capacity, businesses especially those small ones, should be better educated on ways to effectively cope with disaster emergencies.

The quasi-experimental design used in this paper serves to provide a complementary framework to the time series analysis in the current disaster impact literature. ARIMA intervention models offer a parsimonious way to exploit a relatively long time series when data on other variables are limited. Past local economic impact studies relies on data collected at the state-level as controls for overall macroeconomic dynamics (i.e., Ewing et al. 2005; Baade et al. 2007). State-level data are arguably inferior, if not invalid, measures of control for local economies hit by a disaster. Local economies are influenced by macroeconomic conditions as well as local characteristics such as their place in the urban spatial hierarchy and local labor and goods market conditions. Moreover, since a state economy is the aggregate of local economies, disaster impacts at local levels may be reflected at the state level. Using a state economy as a control in assessing local economic impacts may result in underestimation. Therefore, the quasi-experimental intervention analysis design provides a better alternative for this type of local disaster impact assessment.

There are a few limitations to our study. First, due to data availability, residential damage and property damage are used to measure the severity of flood damage. These damage figures somehow underestimate the total damage occurred to the flooded counties. Due to different categorizations of flood damage in two data sources, it may not suffice to show accurate perspectives on flood severity on local economy through simple comparisons. For instance, in SHELDUS, for areas prone to significant riverine floods are floodplains; as a result, the property damage may involve little residential activity and most of impacts concentrated in agricultural, transportation and utilities. Such a shortcoming stemmed from inconsistent categorization of flood damage records, however, can only be improved if better data sources become available for future studies. Secondly, we use a 30-mile buffer to control for spatial spillover effect. A task for future research is to actually model spatial autocorrelation instead of exogenously defining a spillover buffer zone. Third, this comparative study is only a preliminary step in understanding local economic impact and its resilience over multiple disaster events. Future research could extend to finer geographic scale, i.e., sub-county level, a broader range of economic variables, i.e., income and employment, and over more repetitive natural disaster events such as seasonal hurricanes. Policy background analysis and interviews of local business owners and residents are also needed to supplement the understanding on how local economy adjusts to natural disasters.

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