Assessing the Economic Impacts of the 2008 Mississippi River Flooding in Southeast Iowa, and West-central Illinois: A Macro-Economic Approach

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Abstract

This paper highlights the economic impact of the 2008 Mississippi River floods for a six-county region in southeastern Iowa (Des Moines, Henry, Lee and Louisa counties) and west central Illinois (Hancock, and Henderson counties). An econometric assessment of personal consumption expenditure in the region reveals a flood-induced reduction in expenditure of $468 mil. Furthermore, the flood lowered employment permanently to a tune of 400 jobs. In economic-impact terminology, these reductions translate into a total loss of $864.67 mil for the industries in the region. The results of this paper should be of interest to policymakers at the local, state, and federal level.

I. Introduction

In June 2008, the Midwest suffered its worst flooding in 15 years causing widespread damage to towns and crops. Twenty six people died and thousands were displaced from their homes (Johnson, 2008). A number of studies have addressed these flood-related losses (see for example, Long Term Recovery Council, 2010; Casagrande, and McIlvaine-Newsad, 2010). However, none has assessed flood impacts on both sides of the Mississippi River spanning Illinois, and Iowa. This study bridges this gap in knowledge. Specifically, it explores flood-induced economic losses in a six-county region in southeastern Iowa (Des Moines, Henry, Lee and Louisa counties) and west central Illinois (Hancock, and Henderson counties).

<u>What is Flood Damage</u>?

The concept of "flood damage' refers to all types of harm caused by flooding. The extant literature categorizes flood damage into direct and indirect damages (see for example, Greenberg, Lahr, and Mantell, 2007). Briefly, *direct flood damage* refers to harm induced by the physical contact of flood water. This includes, for example, damage to buildings, crops, and health impacts. *Indirect flood damages* are caused by disruption to physical and economic linkages. Refinements to the classification include specifying damages in monetary (*tangible damages*), or non-monetary terms (*intangible damages*). An example of the latter would be the inconvenience of post-flood recovery assessed using residents' perceptions about quality of life. Table 1 provides examples of these categories.

Table 1: Flood Damages: Classifications and Examples

	Tangible Measure	**Intangible Measure**
Direct Damage	Damage to: Buildings, and infrastructure	Health impacts of residents Loss of ecological goods
Indirect Damage	Loss of industrial production Traffic disruption	Increased vulnerability of survivors; Inconvenience of post-flood recovery

[1] This report is based on data sources believed to be reliable. However, because of the possibility of human or mechanical error by our sources, we do not guarantee the accuracy of any information and are not responsible for results obtained from the use of such information.

A careful examination of Table 1 reveals difficulties involved in data collection. For example, to assess damages to buildings (a direct, tangible measure) we could utilize market-value measures sourced from taxation databases. But these values often overestimate the actual damage. Underestimation could happen too; historic buildings may have value far greater than their repair and replacement costs. What is needed is a multi-method approach to gathering valid, direct-damage data. For example, post-event field survey of residents and interviews with realtors in the region could be used to construct tangible information on direct flood damages.

In the case of indirect, tangible measures, even field surveys become difficult to implement. For example, consider a scenario where a producer *Z* had to stop production due to flooding in the manufacturing facility. This would economically impact not only *Z* but also its raw material suppliers, and consumers of its products - raw material suppliers need to seek other purchasers, and *Z*'s consumers need to find other consumption alternatives. To assess these losses, we need to trace all of *Z*'s backward (suppliers) and forward (customers) connections or linkages. If there are *i* such producers in the flood affected region, each with *j* suppliers, and *k* customers, then the task becomes one of tracing all i x $j + i$ x k connections. This is extremely difficult and time intensive.

One solution for this difficulty in data gathering is to focus on the macro-economic impact of the disaster (see for example the recommendations of the European Community's FlOODsite report, 2007). For example, the salient component(s) of the Gross Regional Product (GRP)[2] in each of the disaster counties could be analyzed for changes during the flood year. This entails cross-classification of GRP changes by industry to infer flood-impacts on specific industries and in turn the economy. As an illustration, if the retail industry contributed 2% less to the economy during the flood year than the previous year, then we could attribute this negative shift to floods. However, since changes to GRP could be caused by a number of events including flood, we have to utilize statistical approaches to gain insights into the impact of "shocks", if any, to the economy during the flood year.

To elaborate, consider a county with exports accounting for the majority of the county's GRP. Assume that the county is afflicted by a natural disaster at time *t*. How could we account for the impact of the disaster on the county's economic systems? A simple, macro-economic approach would involve: (i) tests of statistical significance of the disaster on the county's GRP or, in this case one of the GRP components, exports (ii) forecasts of the county's exports for period *t*, (iii) analysis of forecasting errors or computation of "deviation" scores, and (iv) use of deviation scores to assess the resultant contraction in the output of one or more export industries[3]. This approach is employed in this paper. Specifically, it combines the benefits of econometrics, which focuses on relations between variables, with those of time series analysis, which disentangles the dynamics in economic data, to gain insights into flood-related losses.

[2]GRP is composed of personal consumption expenditures, investments, exports, imports, etc. (Leontif, 1951).
[3] See Section III for conceptual models. Deviation-scores could be computed by subtracting forecast GRP values from actual figures. These scores can then be employed to assess changes to output originating in different industries.

The rest of the paper is organized as follows. Section II sets the context of the study by profiling the economic status of the counties. This is followed by a discussion on the modeling aspects of the GRP components in Section III. Section IV presents the results of the modeling work. The question, “by how much did factor payments or value added decrease in these economies” is addressed in Section 5. Finally, Section 6 summarizes the economic impact assessment.

II. **Profile of the Counties (Setting the Context)**

The statistics presented in this section pertains to the six Illinois (IL) and Iowa (IA) counties. Key indicators have been benchmarked against relevant State measures.

We begin with the region’s population as at 2010 and explore its growth rate before and after the floods. Then, we assess the region’s GRP during 2010, highlight the economic strength of the counties, and explore changes to GRP during the flood year compared to the previous year. Finally, we investigate changes in one of the major determinants of GRP, the labor force.

Population

The population of the six-county region in 2010 was 134,154 persons. The population growth in the counties, aftermath the flood, was negative in five of the six counties, and positive in Des Moines (Table 1).

In general, the severity of the post-flood population loss is more pronounced in smaller economies (the rank correlation between population growth rate and GRP is 0.94). Henderson County, IL, the smallest of the six economies, had a five-fold increase in population loss during 2008-2009 compared to the previous periods. In contrast, the largest economy, Des Moines, experienced a slight increase in the growth rate.

To gain additional information about the population changes, we analyzed the migration data of the counties using data obtained from the IRS “County-to-County Migration Data Files” (Table 2). The results highlight a 0.55% population loss due to migration in the six-county region during 2008-2009. Henry, and Louisa, the two IA counties, had higher population outflows.

Table 1: Population

Region	**2010 Population**	**Population Growth Rate (ACGR)**	
		1969-2007	2008-2009
Six-county region	134,154	-.003	-.005
Hancock county, IL	19,104	-.006	-.011
Henderson, IL	7,331	-.003	-.015
Total Illinois	12,830,632	.004	-.005
Des Moines, IA	40,325	-.004	.006
Henry, IA	20,145	.003	-.007
Lee, IA	35,862	-.005	-.001
Louisa, IA	11,387	.002	-.039
Total Iowa	3,046,355	.002	.002

Source: www.factfinder2.census.gov; BEA’s Regional Economic Accounts

Table 2: Migration Analysis: 2008-2009

	Population		
Region	**Inflow**	**Outflow**	**Net Migration as a Proportion of total population**
Hancock, IL	751	837	-0.47%
Henderson, IL	351	404	-0.72%
Des Moines, IA	1751	1735	0.04%
Henry, IA	829	1051	-1.11%
Lee, IA	1263	1322	-0.17%
Louisa, IA	514	849	-2.98%
Six-county Region	5459	6198	-0.55%

<u>Gross Regional Product by Industry</u>

Figure 1 shows the industry contribution to the six-county region's $5.47 billion economy. These are 2010 estimates derived utilizing BEA data. The largest contribution to GRP in 2010 was made by the Manufacturing Industry (24%). Other significant contributors were Government & Government Enterprises (19%), Healthcare & Social Assistance (11%), Farming (10%), and Retail Trade (7%). Table 2 provides county-wise breakdowns of these numbers.

Table 3 highlights county-wise changes to GRP during the 2008 flood year. Manufacturing sector and farming show declines across the counties. As mentioned earlier, these changes cannot be attributed to flood alone. That kind of inference is statistical-model based and is presented in Sections III and IV. Here, the purpose is one of profiling the region; setting the background for statistical inference.

Figure 1: Gross Regional Product: The Six-County Region, 2010 Estimates

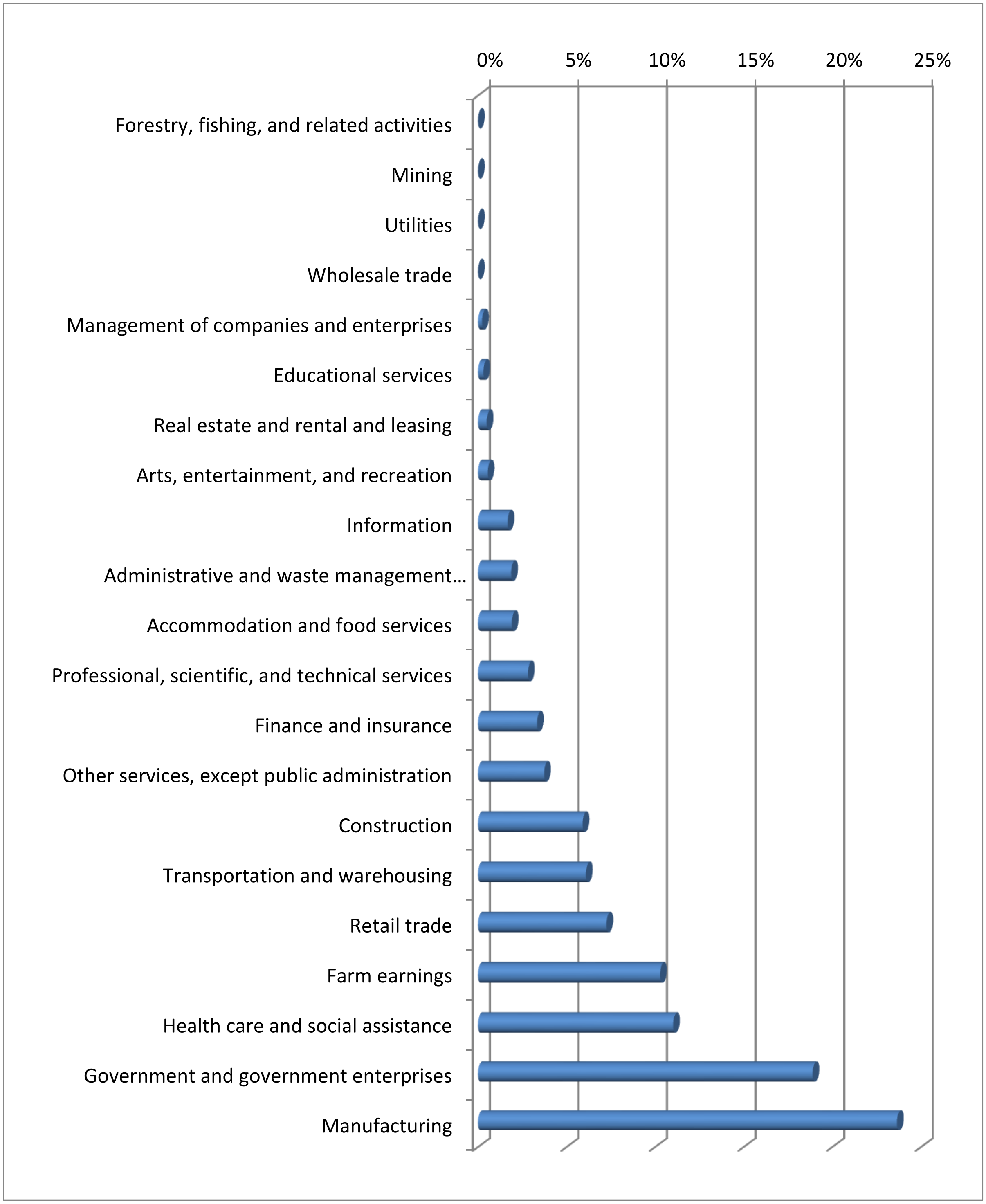


Table 2: Estimated 2010 Gross Regional Product (Level $m)

Industry	Hancock	Henderson	All IL	Des Moines	Henry	Lee	Louisa	All IA
Farm earnings	214	121	6,726	49	73	27	60	8,907
Forestry, fishing, and related activities	0	0	578	0	0	2	0	531
Mining	0	0	5,488	0	0	1	0	275
Utilities	11	0	5,446	0	2	16	0	1,335
Construction	44	0	32,073	100	63	87	19	7,790
Manufacturing	91	0	73,163	484	73	430	171	21,917
Wholesale trade	33	27	40,337	0	34	35	23	7,569
Retail trade	39	13	33,920	152	63	100	15	9,066
Transportation and warehousing	22	18	25,618	153	38	91	0	5,667
Information	6	0	17,402	18	51	8	4	3,019
Finance and insurance	30	0	54,524	51	42	40	13	12,106
Real estate and rental and leasing	2	0	11,299	12	4	7	1	1,250
Professional, scientific, and technical services	44	0	77,563	56	22	28	0	6,328
Management of companies and enterprises	0	0	19,617	6	3	3	0	1,904
Administrative and waste management services	5	3	25,121	48	8	25	10	3,673
Educational services	0	0	12,151	5	2	9	0	1,891
Health care and social assistance	0	24	66,336	301	57	179	20	14,902
Arts, entertainment, and recreation	0	0	5,894	9	4	15	1	1,051
Accommodation and food services	0	0	16,915	51	20	26	4	3,232
Other services, except public administration	50	0	25,029	49	47	35	17	4,925
Government and government enterprises	157	81	96,321	247	171	235	108	24,425
GRP	749	287	651,518	1,798	777	1,402	465	142,698

Note:
GRP was estimated based on personal income distribution in the region. Source: GDP by industry data table: GDPbynd_VA_NAICS (http://www.bea.gov/industry/gdpbyind_data.htm).

Table 3: Percentage Changes to County Gross Regional Product: 2007 to 2008

Industry	Hancock	Henderson	All IL	Des Moines	Henry	Lee	Louisa	All IA
Farm earnings	-7%	-24%	-24%	-6%	-39%	-19%	-17%	-11%
Forestry, fishing, and related activities	0	0	9%	0	0	0	0	8%
Mining	0	0	-9%	0	0	0	0	0%
Utilities	28%	10%	3%	0	0%	7%	0	5%
Construction	-13%	0	-13%	-2%	-14%	-13%	-20%	-11%
Manufacturing	-27%	-100%	-7%	-2%	-4%	-3%	2%	-5%
Wholesale trade	17%	44%	-2%	0	5%	6%	-22%	1%
Retail trade	10%	10%	-2%	4%	-1%	5%	6%	3%
Transportation and warehousing	11%	16%	-2%	-4%	5%	-3%	0	0%
Information	3%	0	-3%	-4%	64%	3%	4%	0%
Finance and insurance	8%	0	-3%	5%	5%	6%	2%	3%
Real estate and rental and leasing	4%	0	-2%	5%	-12%	-1%	0%	2%
Professional, scientific, and technical services	15%	0	-1%	-4%	8%	2%	0	4%
Management of companies and enterprises	0	0	2%	8%	15%	29%	0	2%
Administrative and waste management services	16%	4%	-8%	10%	-4%	-13%	-10%	1%
Educational services	0	0	11%	8%	3%	-10%	0	8%
Health care and social assistance	0	22	8%	8%	6%	9%	11%	7%
Arts, entertainment, and recreation	-100%	0	0%	5%	9%	-2%	-8%	-1%
Accommodation and food services	-100%	0	1%	2%	1%	5%	-3%	2%
Other services, except public administration	15%	0	2%	5%	0%	-1%	3%	4%
Government and government enterprises	24%	19	8%	10%	5%	9%	10%	8%
GRP 2008 ($ mil)	-0.02 $726	-0.03 $279	-0.01 631,970	0.02 $1,68	-0.03 $741	0% $1,337	-.02 443	0.01 136,062

Note:
GRP was estimated based on personal income distribution in the region.
Source: GDP by industry data table: GDPbynd_VA_NAICS (http://www.bea.gov/industry/gdpbyind_data.htm)

Labor Force
The estimated number of employed and unemployed persons in the six-county region during 2010 was 67, 514. Changes to employment numbers in the counties, aftermath the flood, were in the range of 0% to -5% with the largest number of unemployed persons residing in the large IA counties of Des Moines, and Lee (Table 4, and Figure 2).

Table 4: Labor Force: Number of Employed and Unemployed Persons

Region	**2010**	**2007**	**2008**	**% Change: 2007-2008**
Hancock	9915	9939	9878	-1%
Henderson	3843	4041	3918	-3%
Des Moines	21048	21113	20906	-1%
Henry	9431	10337	10173	-2%
Lee	17354	17376	17489	1%
Louisa	5923	6446	6381	-1%
Total	67514	69252	68745	-1%

Figure 2: Changes to Unemployed Persons: 2007 to 2008

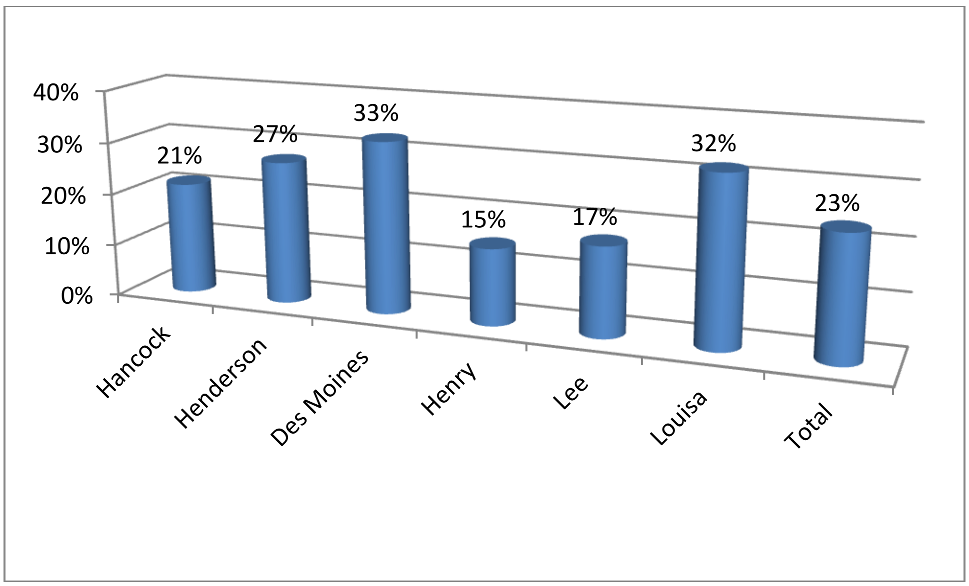


Figure 2 shows changes to unemployment numbers in the counties. Combined with Tables 1 and 2 on population and migration, Figure 2 suggests that during tough economic times, people seek refuge and employment in large population centers.

Finally, Table 5 highlights industry-employment numbers, county-wise. As one would expect, larger the county's population, less is its reliance on the farming industry for employment.

Table 5: Employees by Industry – 2010, County-wise Data

Industry	Hancock	Henderson	Des Moines	Henry	Lee	Louisa
Farming	12%	15.1%	2%	6%	4%	11%
Forestry, fishing, and related activities					1%	
Mining					<.5%	
Utilities	<.5%				<.5%	
Construction	6%		5%	5%	6%	5%
Manufacturing	7%		16%	15%	19%	27%
Wholesale trade	3%	6.0%			2%	3%
Retail trade	10%	9.3%	14%	10%	12%	6%
Transportation and warehousing	3%	4.8%	5%	10%	4%	
Information	1%		1%	1%	1%	1%
Finance and insurance	6%		4%	3%	3%	3%
Real estate and rental and leasing	2%		2%	2%	2%	2%
Professional, scientific, and technical services	4%		3%	4%	2%	
Management of companies and enterprises	0%		0%	1%	0%	
Administrative and waste management services	3%	3.0%	4%	3%	4%	4%
Educational services			1%		1%	
Health care and social assistance		7.3%	14%		13%	7%
Arts, entertainment, and recreation			2%	1%	2%	1%
Accommodation and food services			7%	4%	6%	3%
Other services, except public administration	8%		5%	5%	5%	4%
Government and government enterprises	16%	17.3%	11%	16%	12%	15%
Total employment	8,823 (100%)	3,470 (100%)	19,508 (100%)	8,585 (100%)	15,875 (100%)	5,509 (100%)

Note: Blank cells denote confidential data masked by the BEA. Source: Estimates based on Table CA25N Total full-time and part-time employment by NAICS industry 1, Bureau of Economic Analysis.

In summary, the six-county region is faced with decreasing population. One-quarter of its $5.47 billion economy relies on the manufacturing industry. If one compares the region's GRP for 2008 with that of 2007, it is clear that farm earnings, and manufacturing had negative growth. The next two sections explore the role of the 2008 floods in these declines.

III. Modeling the Economic Impact: Conceptual Foundations

In this section, we conceptualize the economic impact of the 2008 flooding using a combination of algorithmic formulae, and linear and nonlinear modeling.

Consider Table 6. It shows the "final demand" components of the Input-Output (IO) transaction table for each of the six counties - final demand show the sales of the producing industries in the counties to various final users. Since personal consumption expenditure (*C*) is the salient component for all of the counties, we model *C* to assess the economic impact of flooding in the counties.

Table 6: Final Demand Components for the Counties: 2010 IO Table Estimates

County	**% of GRP**				**GRP ($Mil)**
	Personal Consumption Expenditure	**Government Consumption Expenditure**	**Investments**	**Exports**	
Hancock, IL	77	12	15	-4	749
Henderson, IL	79	11	13	-3	287
Des Moines, IA	72	15	18	-5	1,798
Henry, IA	73	14	17	-4	777
Lee, IA	74	14	17	-5	1,402
Louisa, IA	75	13	16	-4	465

Source: http://www.bea.gov/regional/

Modeling Personal Consumption Expenditure[4]

The functional relationship of aggregate consumer expenditures to income is one of the core areas in the study of macroeconomic dynamics (Draby 1974; Merz et al 2010). In general, the micro-behavioral equation for *C* at the household level at time *t* is:

$$c_{it} = \alpha + \beta y_i + u_i \qquad \text{for i=1,2,…,N} \qquad (1)$$

where c_{it} = personal consumption expenditure of the i^{th} household at time *t*;
y = personal income, and u_i is the disturbance term assumed to be independent with common variance λ^2.

[4] The empirical definition of *C* includes pure consumption and purchases of consumer durable and semi-durable goods (Draby, 1974).

The aggregate consumption function at the county level assuming that α, β, and λ^2 are the same for all of the households, is the sum of EQ 1:

$$\sum_{i=1}^{N}[c_{it} = \alpha + \beta y_i + u_i] \text{ , which can be expressed as} \quad (2)$$

$$C = \alpha N + \beta Y + U, \quad \text{where, } \sigma^2(U) = N\,\lambda^2. \quad (3)$$

Estimating EQ 3 by least squares require constant residual variance. Therefore we apply the weight $N^{1/2}$ to EQ 3 to obtain:

$$\frac{C}{\sqrt{N}} = \alpha\sqrt{N} + \frac{\beta Y}{\sqrt{N}} + \frac{U}{\sqrt{N}} \quad (4)$$

EQ 4 shows how the population variable *N* should be assessed at the macro level given the restrictive micro-behavioral conceptualization of EQ 1. Appendix 1 provides empirical evidence in support of EQ 4. Specifically, the residual analysis in Appendix 1 reveals that $\widehat{U_t}$ are correlated instead of independent as assumed, and the variance σ^2 of U_t is not constant.

<u>Pool the Time-Series data</u>?
The next issue in estimating EQ 4 is the pooling of time-series data; do we pool the six counties, 20-years data series for each county, and estimate EQ 4 using 120 observations? To address this question, we utilize the *F* ratio to test the hypothesis of homogeneity of regression for the six counties:

H_0: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6$
$\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6$

The *F* ratio is given by:

$$F = \frac{\frac{(S_2 - S_1)}{(2N-2)}}{\frac{S_1}{\sum_{i=1}^{6} T_i - 2N}},$$

where, S_1 = Unrestricted residual sum of squares; aggregate residual sum of squares of the six county-level models;
S_2 = Restricted residual sum of squares; sum-of-squares obtained from the pooled regression;
N is the number of linear restrictions implied by H_0, and
T_i indicates the 20 years (1990-2009) time series for each of the *i* = 1 to 6 counties.

The results shown in Appendix 2 suggest that the computed $F_{\alpha=.05,\ 10,\ 108} = 20.75$, is significant at the p= (5.87699) x (10^{-21}) level. Since the *F* test suggests significant differences in the coefficients, we do not pool the data.

Flood-Induced Shock to the Economy

We hypothesize differences in model parameters for the flood years; since flooding is an inconvenience we believe that the consumption function would show a parallel downward shift during the flood year(s). To test this hypothesis, we conceptualize EQ 3 as follows:

$$\begin{Bmatrix} C1 \\ C2 \end{Bmatrix} = \alpha_1 \begin{Bmatrix} 1 \\ 1 \end{Bmatrix} + (\alpha_2 - \alpha_1) \begin{Bmatrix} 0 \\ 1 \end{Bmatrix} + \beta_1 \begin{Bmatrix} y_1 \\ y_2 \end{Bmatrix} + U \text{ , or}$$

$$C = \alpha_1 - (\alpha_2 - \alpha_1) D_1 + \beta_1 Y + U \text{, where} \qquad (5)$$

D_1 = 1 for all observations in period 1 or non-flood years; 0 otherwise.
The coefficient D_1 measures the change in the intercept from period 1 to period 2. A statistically significant D_1 is required to infer shifts in *C* during the flood years.

Time Series Models

To ensure construct validity of the concept of flood-induced economic impact, we assess the impact of flooding using two, additional time-series: employment, and net migration[5]. We model these series using autoregressive processes, an ARIMA (*p*,*d*,*q*) model with a transfer function analysis of flooding (see Appendix 3). Specifically, we assess the pulse or the temporary effect of floods that disappears gradually, and a step or permanent effect.

Variable Definitions and Data Sources

County-level information is scarce. Often, one needs to compute proxies of variables using national and state level data. For example, to calculate the GRP of a county, we start with the state GRP data. Then, based on personal income of the county, allocate a proportion of the state GRP to the county. Similarly, to relate county GRP to industry, personal income derived from industry is used as the allocation weight. Table 7 shows the operational definitions of key variables used in the study. Throughout the document, where feasible, data sources are footnoted for Tables, and Figures.

[5] Construct validity is established when all of the ARIMA models, and the consumption function model show flood effects.

Table 7: Variables Operational Definitions

Variable	Label	Type	Operational Definition	Source
Consumption expenditure	*C*	County level, annual data for the period 1990-2009	Pure consumption of households including durable and non-durable purchases. "Weights" derived from Consumer Expenditure Survey Tables were used for county-level allocations of expenditure.	1990-2009 Consumer Expenditure Survey Tables, Bureau of Labor Statistics; County- wise Income Group Distribution, American Community Survey, US Census Bureau
Personal income	*Y*	County level, annual data for the period 1990-2009	Income that is received by all persons from all sources.	County Personal Income and Employment Tables, Regional Economic Information System, Bureau of Economic Analysis.
Population	*N*	County level, annual data for the period 1990-2009	Census Bureau midyear population estimates. Estimates for 2000-2009 reflect county population estimates available as of April 2010.	Bureau of County Personal Income and Employment Tables, US Department of Commerce.
Net Migration	*M*	County level, annual data for the period 1990-2009	Population inflows less outflows.	IRS County-to-County Migration Data.
Employment	*E*	County level, monthly time series for 2001-2010.	Number of employed persons.	Local Area Unemployment Statistics, Bureau of Labor Statistics.
Gross Regional Product (GRP)	*GRP*	County level, annual data for the period 1990-2009	State GDP allocated to counties based on personal income in the county.	GDP by States, Regional Economic Information System, Bureau of Economic Analysis.

IV. Results of Model Estimation

The deflated EQ 4 produced high R^2 but did not improve the Durbin-Watson statistic (Appendix 4). In addition, the residuals exhibited a pattern often found in mis-specified equations: a ratchet pattern that denotes correlation among the residuals (Granger and Newbold, 1974). To address this 'auto correlation' problem, we resorted to estimating the equations in first-difference form. Specifically, we regressed ($C_t - C_{t-1}$) on ($y_t - y_{t-1}$). The assumption is that the first-differences of residuals are uncorrelated among themselves. Since the constant term disappears in the subtraction, we estimate the equation:

$$C_t - C_{t-1} = \beta\,(y_t - y_{t-1}) + \gamma_1 D_1 + (U_t - U_{t-1}) \qquad (6)$$

Table 8 shows the results of this exercise. While the income variable is significant in all of the county-level equations, the indicator variable used to assess differences in intercepts during flood years is insignificant for Hancock, and Louisa counties. What this indicates is that flooding did not reduce personal consumption expenditure in these two counties. Although this finding will be scrutinized with Chow test later in the Section, for the present it is assumed nil or no flood-induced, negative economic impacts for Hancock, and Louisa.

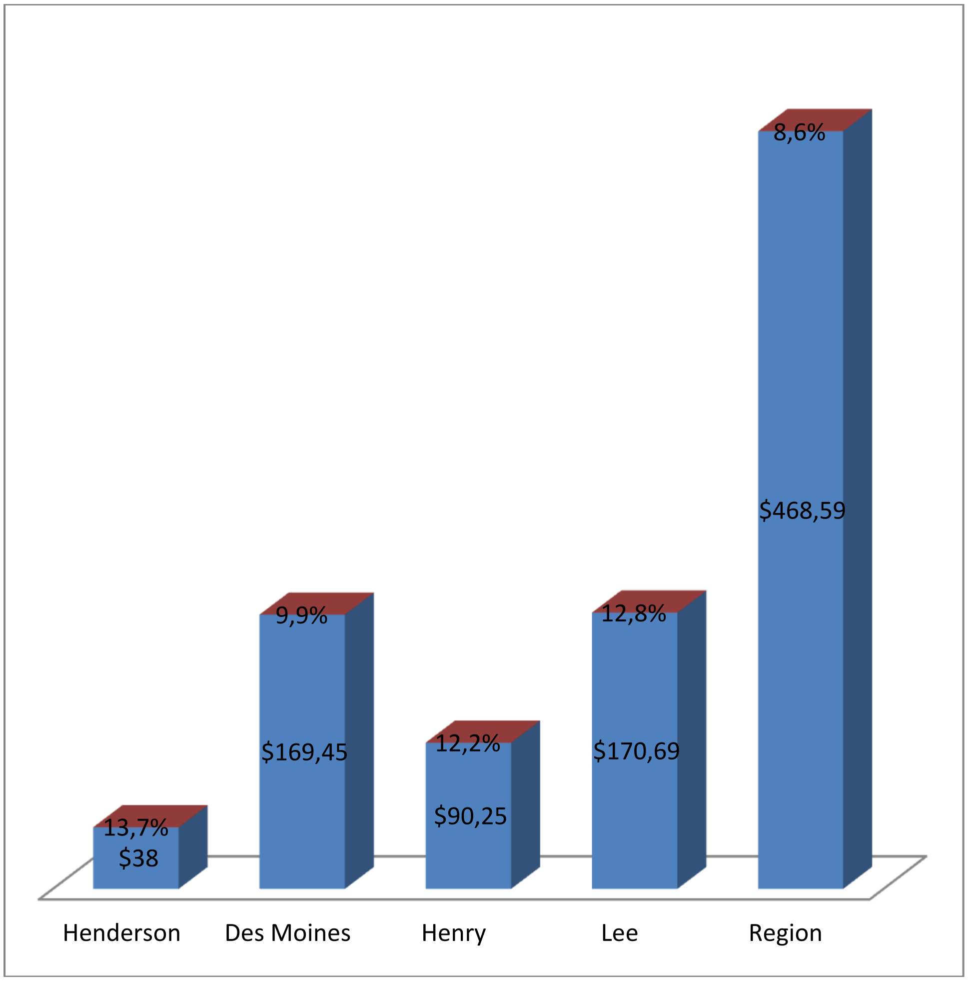
Table 8: Parameter Estimates: Results of First-Difference, County-Level Regressions

County	$\hat{\boldsymbol{\beta}}$	γ_1	**DW**	$\mathbf{R^2}$
Hancock, IL	0.74 (4.84)	4636.14 (0.33)	2.03	.55
Henderson, IL	0.81 (5.37)	-17927.45 (-2.78)	1.7	.65
Des Moines, IA	1.21 (3.7)	-69715.89 (-2.14)	2.04	.52
Henry, IA	0.85 (3.29)	-40347.9 (-2.61)	1.7	.48
Lee, IA	0.8 (2.45)	-76270.27 (-2.57)	1.7	.40
Louisa, IA	0.98 (6.17)	-10902.41 (-1.7)	1.71	.70

Note: D_1 is the indicator variable that measures parallel shifts in the intercepts during flood years (see Section III). Figures in parentheses are *t* ratios.

Figure 3 shows the flood-induced reduction in personal consumption expenditure in the six-county region. In all, we estimate the total reduction to be around $468 mil, or approximately 9% of the region's GRP. While on a dollar basis the reduction in consumption expenditure is more pronounced in the larger counties of Des Moines, and Lee, it is the smaller community of Henderson, IL that suffered the most in terms of reduction in GRP.

Figure 3: Flood Related Reductions in Personal Consumption Expenditure: Monetary Value and as a Percentage of GRP



In order to explore the best and worst scenarios of flooding; often floods do provide positive economic benefits to a region in terms of public and private financial assistance to households and businesses, we built a 95% confidence interval around our prediction equation. The results suggest that smaller communities such as Henry, IA might have benefited from the floods (Table 9)[6].

[6] Because we allocated personal consumption expenditure to counties based on personal income (see Table 7), we assume it to be a sample. Our 95% confidence interval implies that if we calibrate our prediction equation repeatedly with different samples, then in 95% of all the samples the interval given will include the true value.

Table 9: Best and Worst Scenarios of Floods: Prediction Intervals for Personal Consumption Expenditure ($mil)

County	Point Estimate	Best Scenario	Worst Scenario
Henderson, IL	($38.2)	$6.15	($82.53)
Des Moines, IA	($169.45)	($70.89)	($268.02)
Henry, IA	($90.25)	$58.47	($238.98)
Lee, IA	($170.69)	($123.50)	($217.80)
Total for the region	($468)	($129.77)	($807.33)

Predictive Accuracy of the County-Level Models

To assess the predictive accuracy of the econometric models, we utilized two measures: (i) Mean-square error (MSE) decomposed into bias, regression and disturbance proportions, and (ii) Theil's U_1 statistic (Theil, 1966). The results shown in Table 10 suggest little or no bias in our prediction models.

MSE is defined as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\frac{(P_t - A_t)^2}{A_{t-1}},$$

where P_t is the predicted value at time *t*, and A_t is the actual value at *t*. This can be expressed as:

$$MSE = (\bar{P} - \bar{A})^2 + S_{P-A}^2$$

The first term in the RHS is called the *bias* component of MSE: it indicates the tendency of the model to estimate too high or too low a level of the forecast variable. The variance of the prediction errors, the second-term in the equation, can also be decomposed. If we let ρ denote the correlation between *A* and *P*, we have the identities:

$$S_{P-A}^2 = S_P^2 + S_A^2 - 2\rho S_P S_A$$

$$S_{P-A}^2 = (S_P - \rho S_A)^2 + (1 - \rho^2)S_A^2$$

Theil (1966) defines $(S_P - \rho S_A)^2$ the *regression* component, and $(1 - \rho^2)S_A^2$ the *disturbance* term. As regards Theil's U_1, it ranges from 0 to 1 with lower scores denoting more predictive accuracy.

Table 10: Accuracy of Forecasts

Model for ….	**Bias Component**	**Disturbance Component**	**U_1**
Hancock, IL	.0007	3.39579E-05	.15
Henderson, IA	.0026	6.35685E-05	.17
Des Moines, IA	.0275	1.42265E-05	.17
Henry, IA	.0046	3.21331E-05	.29
Lee, IA	.0055	1.78773E-05	.37
Louisa, IA	.0020	6.09698E-05	.16

Alternative Tests for Flood Impacts

Earlier, we tested differences in personal consumption expenditures during flood years and non-flood years using an indicator variable approach. Chow (1960) suggests another variant to this approach, an *F* test based on linear restrictions of parameters.

To elaborate, assume that we believe that flood not only reduces a community's consumption expenditure but also the shape of the community's consumption function. In this situation, we would test the stability of the regression coefficients during flood, and non-flood years. Put simply, we want to test whether the flood-year observations have been generated by the same model.

The *F* test involves constructing residual sum of squares (RSS) for models calibrated with and without flood-year data. If RSS_1 denotes residual sum of squares for model calibrated without the flood year data (n_1 observations), and RSS for all the observations ($n_1 + n_2$), then

$F = \frac{(RSS - RSS_1)}{n_2} \frac{(n_1 - k - 1)}{RSS_1}$ is an F variate with degrees of freedom n_2, n_1-k-1.

Table 11 shows the results of the test for stability of coefficients. For Hancock, IL, we accept the hypothesis that the flood-year observations came from the same model. For Louisa, there was little or no change in personal consumption expenditure during the flood year, but the pace at which they consumed changed. Put another way, the population of Louisa did not consume at the same pace or speed during the flood year as compared to "normal" years. This conclusion is based on our earlier finding that there was no downward shift in personal consumption expenditure in the county (see Table 8). In summary, Table 11 confirms our earlier findings that the flood-year lowered personal consumption expenditure in Henderson, Des Moines, Henry, and Lee counties.

Table 11: Test for Stability of Regression Coefficients: Flood versus Non-Flood Years

County	RSS1	RSS	F Ratio	p
Hancock, IL	6.33E+09	6.41E+09	0.094078564	0.900
Henderson, IL	4.56E+08	2.06E+09	26.39573144	0.000
Des Moines, IA	1.47E+10	4.20E+10	13.93290692	0.000
Henry, IA	2.78E+09	1.12E+10	22.62488003	0.000
Lee, IA	1.03E+10	4.05E+10	21.90471353	0.000
Louisa, IA	8.42E+08	1.58E+09	6.531636036	0.004

Alternative Models: Intervention Analysis of the *M* Series

The *M* series or the net migration series for each of the counties is shown in Table 12. The fitted ARIMA models differ among the counties with the more prominent one being the p=1, q=1, and d=3 process. As mentioned earlier, interventions for the flood year 2008 were modeled using indicator variables (Appendix 3). The results of the ARIMA analysis are given in Table 13. They suggest no intervention or short-term flood effects. This is not surprising since all of the counties have been experiencing migration related population losses for the last five to 20 years.

In addition, the lack of data for post-flood years limits our ability to detect meaningful differences in data.

Table 12: County-Level Net Migration

Year	County					
	Hancock	**Henderson**	**Des Moines**	**Henry**	**Lee**	**Louisa**
1991-1992	415	126	-66	45	53	-258
1992-1993	33	36	-62	-96	-161	252
1993-1994	-97	-92	-110	116	56	-108
1994-1995	33	76	-290	0	7	92
1995-1996	14	56	-127	-80	-222	5
1996-1997	-123	125	-299	-42	-83	-155
1997-1998	12	-11	-139	74	-200	-86
1998-1999	-162	-30	-217	46	-204	-97
1999-2000	-118	39	-337	-122	-14315	-127
2000-2001	-122	8	-304	5	-383	-55
2001-2002	-180	-29	-502	-146	-418	-75
2002-2003	-144	-55	-264	-45	-269	-53
2003-2004	-125	47	-456	-69	-73	-228
2004-2005	-173	-71	-140	29	-40	-220
2005-2006	-99	-63	-164	-71	-113	-22
2006-2007	-83	-13	-52	-13	-203	-45
2007-2008	-150	-46	-182	10	-156	11
2008-2009	-86	-53	16	-222	-59	-335

Table 13: ARIMA Model Estimates: Net Migration Series

County	Constant	AR(1)	AR(2)	AR(3)	MA(1)	MA(2)	MA(3)	Intervention
Hancock, IL: Losing population since 1998-1999	3.538E+005 (1.73)	-1.4008 M_{t-1} (-2.67)	-1 M_{t-2} (-1.87)		1.2638 ε_{t-1} (2.2)	0.99471 ε_{t-2} (1.52)		85.659 x_t^p (0.09)
Henderson, IL: Losing population since 2004-2005	55.16 (.61)	.14 (.26)			-.07 (-1.4)	.67 (2.6)	-1 (-1.56)	-10 (-.009)
Des Moines, IA: Losing population since 1991-1992. Posted a slight increase in 2008-2009	10 (.02)	-1.4 (-2.7)	-1 (-1.8)		1.26 (2.2)	.99 (1.52)		85.66 (.09)
Henry, IA: Losing population since 2001-2002; gained a little in 2007-2008.	35.62 (.51)	.49 (.69)	-.23 (-.26)		-1.2 (-2.27)	1.13 (2.1)	-.92 (-1.8)	-10 (-.02)
Lee, IA: Losing population since 1995-1996; heavy in 1999-2000	10 (.10)	.30 (.32)			-.67 (-1.35)	.67 (1.7)	-1 (-2.26)	-10 (-.001)
Louisa, IA: Exhibits a negative trend in population growth	10 (.10)				-.59 (-1.06)	.66 (2.01)	-.94 (2.67)	-10 (-.01)

Note: Figures in parentheses are *t* statistics.

Alternative Models: Intervention Analysis of the *E* Series

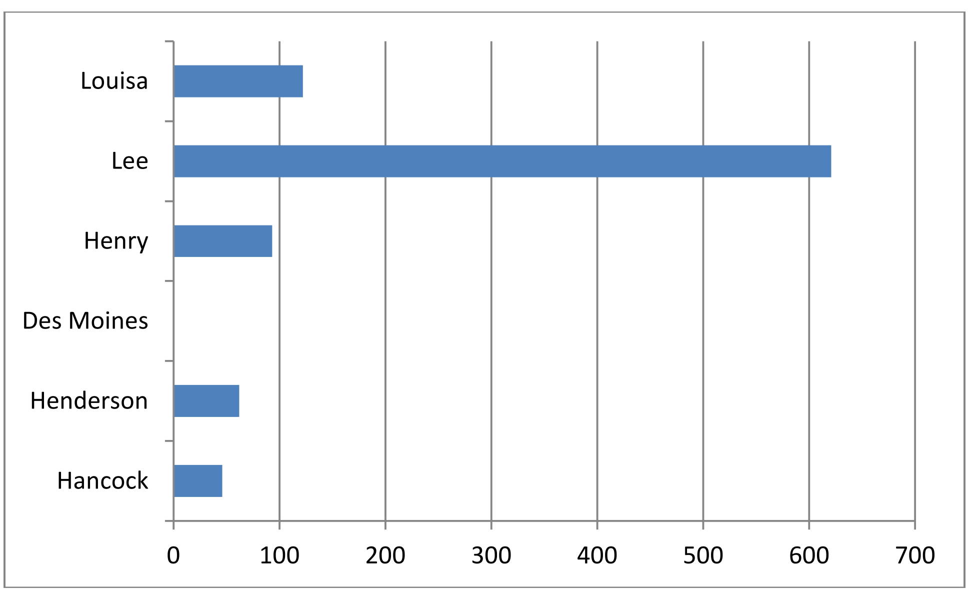
The monthly employment data for the period 2001 to 2010 show stability for IA and a declining trend for IL. With this background in mind, if one looks at the employment growth in the six-county region, it is negative. In other words, these counties have been experiencing declining employment for the last 10 years (Table 14).

Table 14: Employment Growth in the Six-County Region

Region	Total Number of Workers		ACGR
	2001	2010	
Hancock, IL	5,711	4,138	-.0322
Henderson, IL	1212	1131	-.0069
Total IL	5,886,248	5,502,201	-.0067
Des Moines, IA	23,459	20,592	-.013
Henry, IA	10,622	8,992	-.0167
Lee, IA	17,384	15,582	-.0109
Louisa, IA	3,595	3,516	-.0022
Total IA	1,429,543	1,436,029	.00045

Table 15 highlights the results of the ARIMA / ARMA analysis for the counties. These results demonstrate both pulse and step effects of flooding for the counties. For example, Lee County, IA lost 621 jobs during the flood (Figure 4). This pulse effect was followed by a more long-term effect which resulted in the loss of around 214 jobs over the 2009-2010 time periods, (step effect).

Figure 4: Immediate Impacts of Floods (Pulse Effect): Number of Job Losses



Counties with significant, permanent reduction in employment include: Hancock, IL with 150 positions, Des Moines, IA with 239 positions, and Louisa, IA with 8 job losses. Henderson, IL and Henry, IA do not show any permanent effects.

In sum, we estimate the flood-induced reduction in the personal consumption expenditure in the region at around $468 mil, which is approximately 9% of the six-county region's GRP. The next section highlights the economic impact of this reduction in consumption expenditure on the region's industries.

Table 15: ARIMA Model Estimates: Employment Series

County	Constant	AR(1)	AR(2)	AR(3)	MA(1)	Short-Term Effects	Long-Term Effects
Hancock, IL	717.75 (2.5)	.82 E_{t-1} (10.3)	.04 E_{t-2} (.42)			-45.83 x_t^p (>1000)	-149.67x_t^s (-2.2)
Henderson, IL	1.03 (.12)	-.91 E_{t-1} (-18.7)	.88 E_{t-2} (12.67)			-61.77x_t^p (-210)	2x_t^s (.13)
Des Moines, IA	4051 (3.71)	1.04 E_{t-1} (10.88)	-22 E_{t-2} (-2.4)			0x_t^p	-238.9x_t^s (2.03)
Henry, IA	3337.9 (3.03)	.85 E_{t-1} (17.08)	-.23 E_{t-2} (-.26)			92.76x_t^p (5360)	-208x_t^s (-1.8)
Lee, IA	3863.6 (3.35)	.89 E_{t-1} (7.03)	-1.3 E_{t-2} (-.79)	.006 E_{t-3} (.05)		-621.2x_t^p (-1431)	-213.66x_t^s (-2.94)
Louisa, IA	3.12 (3.01)	.48 E_{t-1} (3.7)			-.94ε_{t-1} (-18.3)	-121.75x_t^p (-3.43)	-8x_t^s (-2.3)

Note: Figures in parentheses are *t* statistics.

V. **Economic Impacts**

To assess economic impacts, we relied on estimates from the BEA. Specifically, we first appropriated the $468 mil reduction in personal consumption expenditure in the six-county region (point estimate provided in Table 9) to industries based on personal income sources. For example, if 10% of the total personal income in the region is from agriculture, then $46.8 mil was allocated to agriculture. Label these final demand components, vector F_{15x1}.

Note that this method is far superior to the bridge matrix-based allocation provided by the BEA (see http://www.bea.gov/industry/iotables/table_list.cfm?anon=988995&CFID=6706738&CFTOKEN=7f1eed6a23ad7ba7-AB346D43-00BC-A406-0E27A301200BF78F&jsessionid=a0309dde1fdd58d5014d21671e127a723c25#iotables). Put another way, using the bridge matrix could provide results that are far removed from reality: for example, it might indicate the hospitality sector as a major contributor of GRP in the region when in reality there may be little or no hospitality businesses in the region.

Next, we obtained the total requirement coefficients, the $(I - A)^{-1}_{15x15}$ matrix from (http://www.bea.gov/industry/iotables/options_list.cfm?aggregations_id=0&get_results=show&goto=&anon=995039&CFID=6706738&CFTOKEN=7f1eed6a23ad7ba7-AB346D43-00BC-A406-0E27A301200BF78F&jsessionid=923036dcf90fc6a2497b6774232c735424b3); post-multiplied the vector F to it, and derived the total, industry-wise impacts.

Table 16 shows the industry-wise economic impact of reduction in personal consumption expenditure in the six-county region. Appendix 5 highlights the economic impact for each of the four counties (Henderson, Des Moines, Henry, and Lee). The direct requirement column(s) highlight intermediate demand: for example, in Table 16, the Agriculture sector reduced its inputs in the range of $3.01 mil to $18.7 mil. In all, the agricultural sector contracted by $3.89 mil to $24.18 mil. In all, the total economic impact of flooding for the region's industry was reduction in outputs to a tune of $864.67 mil; the manufacturing industry absorbed around 20% of this reduction.

Table 16: Economic Impact Assessments: The Six-County Region ($ mil)

	Direct Requirement: Point and Interval Estimates			Total Requirement: Point and Interval Estimates		
	Point	**Best**	**Worst**	**Point**	**Best**	**Worst**
Agriculture, forestry, fishing & hunting	-10.8382	-3.00527	-18.6965	-14.0185	-3.88714	-24.1828
Mining	-28.584	-7.92596	-49.3093	-29.0436	-8.0534	-50.1021
Utilities	-10.0833	-2.79597	-17.3944	-20.2325	-5.61021	-34.9024
Construction	-5.46955	-1.51663	-9.43532	-5.46955	-1.51663	-9.43532
Manufacturing	-107.838	-29.9021	-186.028	-184.499	-51.1592	-318.273
Wholesale trade	-16.6848	-4.62646	-28.7823	-35.5959	-9.87026	-61.4052
Retail trade	-1.53663	-0.426088	-2.65079	-47.7883	-13.251	-82.4378
Transportation & warehouse	-16.0105	-4.4395	-27.6192	-26.2026	-7.26563	-45.2012
Information	-14.0603	-3.89873	-24.2549	-37.4871	-10.3947	-64.6676
Finance, insurance, real estate & leasing	-86.0369	-23.8569	-148.419	-199.878	-55.4233	-344.802
Professional services	-75.5798	-20.9573	-130.38	-80.603	-22.3501	-139.045
Educational services	-2.13512	-0.592038	-3.68321	-94.9643	-26.3323	-163.819
Arts & entertainment	-8.00598	-2.21995	-13.8108	-44.9792	-12.4721	-77.5919
Other services	-6.79378	-1.88382	-11.7197	-30.5846	-8.4807	-52.7605
Government	-2.91175	-0.807389	-5.02296	-13.328	-3.69568	-22.9917
Total Impact				-864.67	-239.76	-1491.6

V1. **Summary and Conclusion**

This study focused on the macro-economic impact of 2008 Mississippi River flooding on a six-county region in southeastern Iowa (i.e. Des Moines, Henry, Lee and Louisa Counties) and west central Illinois (Hancock and Henderson Counties). Specifically, personal consumption expenditure: a salient component of the Gross Regional Product in the counties, were analyzed for changes during the flood year. Statistical approaches utilized to gain insights into flood impact include econometric models, and time series techniques.

The results of statistical analyses indicate:

1. The flood-induced reduction in personal consumption expenditure in the six-county region is around $468 mil, approximately 9% of the region's GRP.
2. While on a dollar basis the reduction in consumption expenditure is more pronounced in the larger counties of Des Moines, and Lee, it is the smaller community Henderson, IL that suffered the most in terms of reduction in GRP, approximately 14%.
3. For Louisa, IA, although there was little or no change in personal consumption expenditure during the flood year, the pace or speed at which they consumed changed.
4. Population migration numbers were not affected by the floods. This is not surprising since all of the counties have been experiencing migration related population losses for the last five to 20 years.
5. The number of immediate, flood-related job losses range from 46 to 620 jobs.
6. Flooding also caused permanent reduction in employment in Hancock, IL (150 jobs), Des Moines, IA (239 jobs), and Louisa, IA (8 jobs). Henderson, IL and Henry, IA do not show any permanent job losses.
7. The total direct and indirect economic impact of the 2008 floods is $864.67 mil; the average multiplier is 1.8723.

In conclusion, this study highlights "structural shifts" in the economy of the study region during 2008. These shifts are largely negative and we attribute these to the June 2008 floods.

It is possible that the parameters in our econometric model vary over time because of other influences such as recession, and governmental policy variables. Lack of data prevents us from analyzing these determinants. However, the convergence of findings on employment losses and reduction in personal consumption expenditure add strength to our argument that the 2008 floods caused negative economic impacts in the six-county region.

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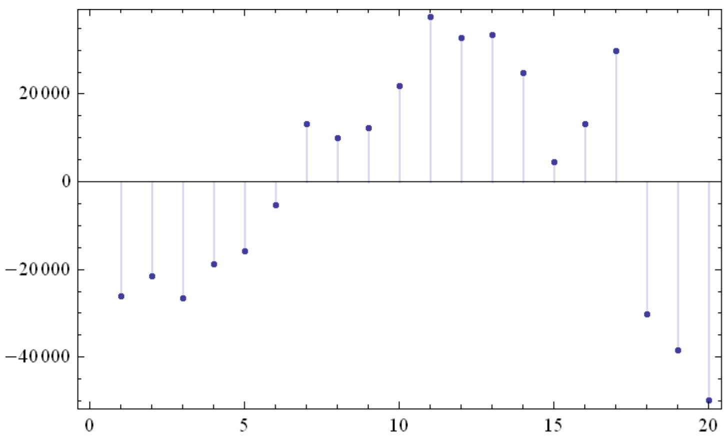
Appendix 1: Test for Violations of Model Assumptions: $\boldsymbol{C = \alpha N + \beta Y + U}$

In order to test EQ 3 for violations of least-squares assumptions, we analyzed the residuals $y - \hat{y}$. Specifically, we calibrated EQ 3 for each of the six counties, list-plotted the residuals, assessed residual correlations (Durbin-Watson Statistic), and examined the sign-pattern of residuals using a contingency table. The findings add validity to our assertion that consumption functions at the macro level should be estimated using weighted-least squares. In the following pages, we present the results of the residual analysis for each of the six counties.

Figure A1: List-plot of Residuals for EQ 3 ($Ct = 32773.2.9 + .975x1(t = 13.23)$; $R^2 = .90$), **Hancock County, IL, 1990-2009)**



Residuals: DW = 0.41

1990	-26190.762	2000	37529.615
1991	-21588.503	2001	32785.229
1992	-26538.319	2002	33350.841
1993	-18812.511	2003	24821.636
1994	-15741.658	2004	4452.618
1995	-5342.9426	2005	13230.07
1996	13056.869	2006	29731.092
1997	9967.9645	2007	-30281.802
1998	12183.887	2008	-38560.364
1999	21892.689	2009	-49945.65

The residual plot shows a systematic pattern in residuals: first positive, then negative, then positive. In addition, the magnitude of the residuals increases with the value of the independent variable, income. The latter is an evidence for $\sigma^2(u_i) \neq 0$. Finally, the residuals, $\widehat{U_t}$ and $\widehat{U_{t-1}}$ are highly correlated (the correlation is .79). The high correlation among the residuals is also confirmed by the sign-pattern test of residuals.

In sum, the residual analysis reveals that $\widehat{U_t}$ are correlated instead of independent as assumed, and the variance σ^2 of U_t is not constant. To tackle these problems, we use EQ 4.

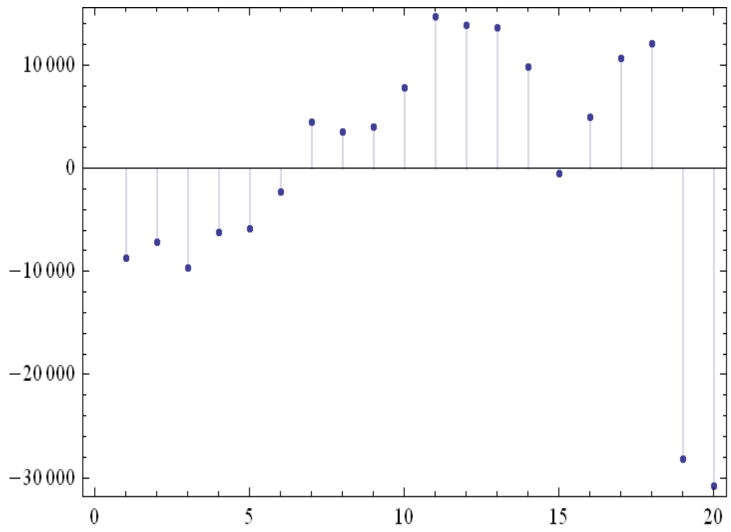
Table A1: Contingency Table for Residuals – Sign-Pattern Analysis (Hancock County, IL)

	Positive at *t*	Negative at *t*
Positive at *t-1*	10	1
Negative at *t-1*	2	7

For $\nu = 1$, and $\alpha = .05$, the computed χ^2 test statistic 10.8 exceeds the critical point set at 5.2. Hence we reject the hypothesis of zero correlation among residuals.

In the following pages we present the residual statistics for all of the remaining five counties.

Figure A2: List-plot of Residuals for EQ 3 ($Ct = 5999.9 + .9995x1(t = 13.47)$; $R^2 = .90$), Henderson County, IL, 1990-2009)



Residuals: DW = 0.625

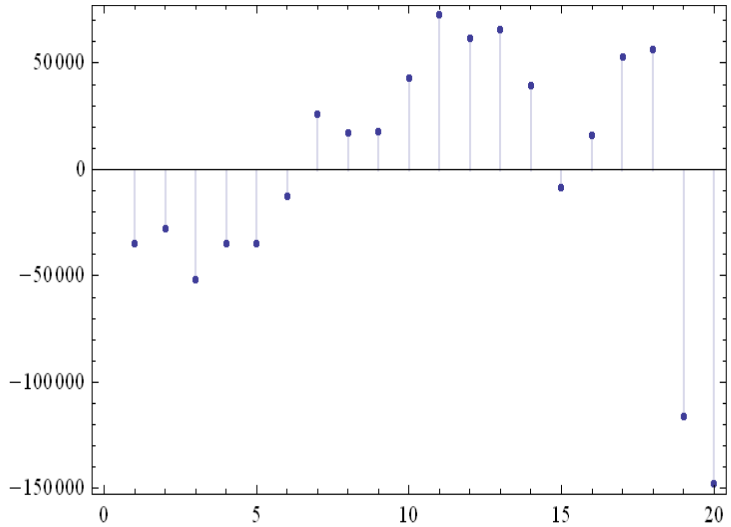
1990	-8695.04	2000	14670.16
1991	-7161.91	2001	13842.16
1992	-9659.56	2002	13656.57
1993	-6207.36	2003	9828.818
1994	-5845.48	2004	-509.395
1995	-2249.97	2005	4966.231
1996	4446.935	2006	10613.39
1997	3480.481	2007	12090.94
1998	3990.192	2008	-28195.9
1999	7810.491	2009	-30871.8

Table A2: Contingency Table for Residuals – Sign-Pattern Analysis (Henderson County, IL)

	Positive at *t*	Negative at *t*
Positive at *t-1*	9	2
Negative at *t-1*	2	7

For $\nu = 1$, and $\alpha = .05$, the computed χ^2 test statistic 7.6 exceeds the critical point set at 5.2. Hence we reject the hypothesis of zero correlation among residuals.

Figure A3: List-plot of Residuals for EQ 3 ($Ct = 24263.3 + .952x1(t = 14.94)$; $R^2 = .92$), Des Moines County, IA, 1990-2009)



Residuals: DW = 0.60

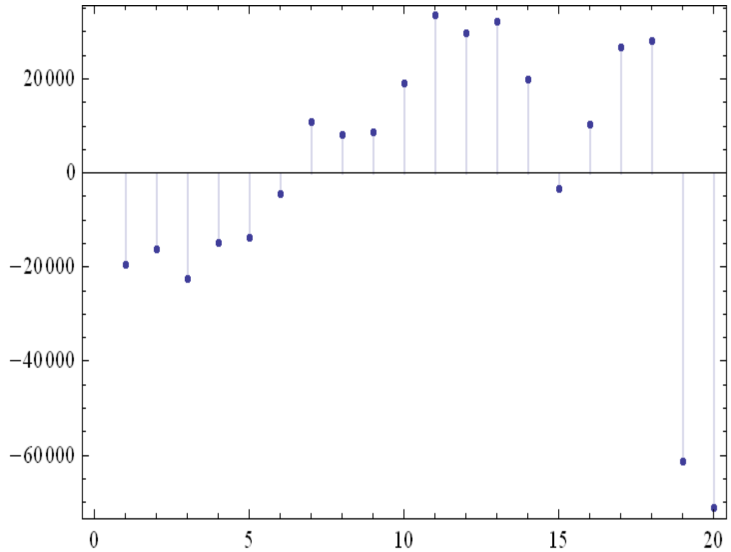
1990	-34546.204	2000	72735.933
1991	-27551.375	2001	61367.648
1992	-51594.852	2002	65960.15
1993	-34630.701	2003	39530.836
1994	-35019.215	2004	-8460.7227
1995	-12836.608	2005	15991.917
1996	26029.472	2006	53165.791
1997	17045.601	2007	56371.464
1998	17874.898	2008	-116317.72
1999	42741.526	2009	-147857.84

Table A3: Contingency Table for Residuals – Sign-Pattern Analysis (Des Moines County, IA)

	Positive at *t*	Negative at *t*
Positive at *t-1*	9	2
Negative at *t-1*	2	7

For $\nu = 1$, and $\alpha = .05$, the computed χ^2 test statistic 7.6 exceeds the critical point set at 5.2. Hence we reject the hypothesis of zero correlation among residuals.

Figure A4: List-plot of Residuals for EQ 3 ($Ct = 8554.76 + .984x1(t = 14.98)$; $R^2 = .92$), Henry County, IA, 1990-2009)



Residuals: DW = 0.62

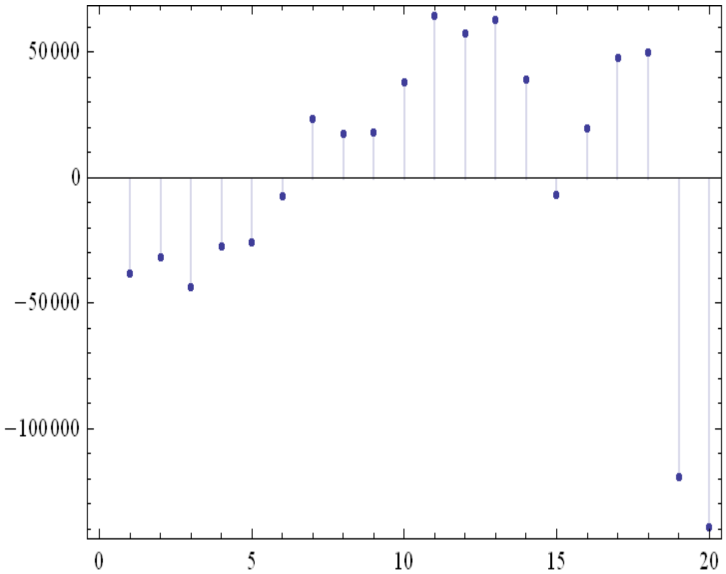
1990	-19496.615	2000	33476.213
1991	-16226.989	2001	29710.383
1992	-22407.964	2002	32123.028
1993	-14757.393	2003	19988.771
1994	-13831.294	2004	-3466.6074
1995	-4498.4081	2005	10277.873
1996	10930.115	2006	26707.672
1997	8169.8312	2007	28130.205
1998	8720.1661	2008	-61304.033
1999	19020.276	2009	-71265.23

Table A4: Contingency Table for Residuals – Sign-Pattern Analysis (Henry County, IA)

	Positive at *t*	Negative at *t*
Positive at *t-1*	9	2
Negative at *t-1*	2	7

For $\nu = 1$, and $\alpha = .05$, the computed χ^2 test statistic 7.6 exceeds the critical point set at 5.2. Hence we reject the hypothesis of zero correlation among residuals.

Figure A5: List-plot of Residuals for EQ 3 ($Ct = 13882.4 + .997x1(t = 11.7)$; $R^2 = .87$), Lee County, IA, 1990-2009)



Residuals: DW = 0.62

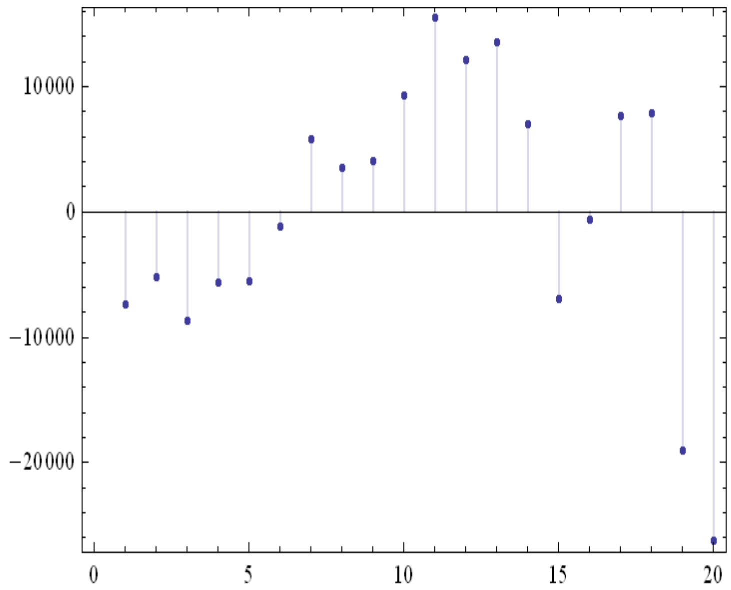
1990	-38213.249	2000	64569.163
1991	-31413.136	2001	57316.221
1992	-43345.424	2002	62779.196
1993	-27469.636	2003	39093.544
1994	-25802.036	2004	-6557.1095
1995	-7167.0551	2005	19481.371
1996	23662.83	2006	47914.938
1997	17514.861	2007	50195.812
1998	18211.433	2008	-119509.14
1999	38201.902	2009	-139464.48

Table A5: Contingency Table for Residuals – Sign-Pattern Analysis (Lee County, IA)

	Positive at *t*	Negative at *t*
Positive at *t-1*	9	2
Negative at *t-1*	2	7

For $\nu = 1$, and $\alpha = .05$, the computed χ^2 test statistic 7.6 exceeds the critical point set at 5.2. Hence we reject the hypothesis of zero correlation among residuals.

Figure A5: List-plot of Residuals for EQ 3 ($Ct = -7953.23 + .992x1(t = 25.8)$; $R^2 = .97$), Louisa County, IA, 1990-2009)



Residuals: DW = 0.57

1990	-7381.4844	2000	15497.317
1991	-5246.4582	2001	12183.037
1992	-8711.5434	2002	13603.485
1993	-5676.7007	2003	7007.6959
1994	-5577.1789	2004	-6971.9758
1995	-1110.6488	2005	-671.03238
1996	5815.3765	2006	7697.859
1997	3503.4639	2007	7930.2381
1998	4045.7972	2008	-19017.593
1999	9356.4096	2009	-26276.063

Table A6: Contingency Table for Residuals – Sign-Pattern Analysis (Louisa County, IA)

	Positive at *t*	Negative at *t*
Positive at *t-1*	8	2
Negative at *t-1*	2	8

For $\nu = 1$, and $\alpha = .05$, the computed χ^2 test statistic 7.2 exceeds the critical point set at 5.2. Hence we reject the hypothesis of zero correlation among residuals.

Appendix 2: *F* Test for Pooling Time-Series Data

Consider the regression of the form:

$c_{it} = \alpha + \beta y_{it} + u_{it}$ for $i = 1$ to 6 counties, and $t = 1990, \ldots, 2009$

where c_{it} = personal consumption expenditure of the i^{th} county at time t;
y = personal income, and u is the disturbance term assumed to be independent with common variance σ^2.

Define, $W_{yyi} = \sum_t (y_{it} - \overline{y_\iota})^2$

$W_{yci} = \sum_t ((y_{it} - \overline{y_\iota})(c_{it} - \overline{c})$

$W_{cci} = \sum_t (c_{it} - \overline{c_\iota})^2$

Then, $\widehat{\beta} = \frac{W_{yci}}{W_{yyi}}$ and $\alpha = \bar{c} - \hat{\beta}\bar{y}$.

The residual sum of squares is $W_{cci} - \frac{{W_{yci}}^2}{W_{yyi}}$ which has $(T_i - 2)$ degrees of freedom.

To test H_0: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6$

$\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6$,

we estimate $c_{it} = \alpha + \beta y_{it} + u_{it}$ based on $\sum T_i$ observations. Let $\bar{C}$ and $\bar{Y}$ be the overall means of the variables. Then,

$T_{yyi} = \sum_t (y_{it} - \overline{Y_\iota})^2$

$T_{yci} = \sum_t ((y_{it} - \overline{Y_\iota})(c_{it} - \overline{C})$

$T_{cci} = \sum_t (c_{it} - \overline{C_\iota})^2$

Then, $\widehat{\beta} = \frac{T_{yci}}{T_{yyi}}$ and $\alpha = \bar{C} - \hat{\beta}\bar{Y}$.

The residual sum of squares is $T_{cci} - \frac{{T_{yci}}^2}{T_{yyi}}$ which has $(\sum T_i - 2)$ degrees of freedom.

We test the homogeneity of the county-level parameters using the $(2i$-$2)$ linear restrictions given in H_0. Specifically, we use the *F* test:

$$F = \frac{\frac{(RRSS - URSS)}{(2i-2)}}{\frac{URSS}{(\sum_i T - 2i)}}$$

where, RRSS is the restricted residual sum of squares, and URSS is the unrestricted residual sum of squares.

Table A1 shows the *F* test computations. Based on these, we reject H_0 that the relationship among parameters is stable.

Table A1: RRSS, URSS, and the *F* Ratio

Region	**Model RSS**
Total – All Counties - URSS	1.67325E+11
All Observations - RRSS	4.88936E+11
F Ratio	$F = \frac{\frac{(RRSS - URSS)}{(2N-2)}}{\frac{URSS}{\sum_{i=1}^{6} T_i - 2N}} = \frac{\frac{(4.88936\text{E}+11 - 1.67325\text{E}+11)}{(12-2)}}{\frac{1.67325\text{E}+11}{120-12}} = 20.75$

Note: F Ratio p Value for [20.75847823,10,108] $\rightarrow 5.87699 \times 10^{-21}$

Appendix 3: Autoregressive Methods

Consider an autoregressive-moving-average model of the sort:

$$x_t - \varphi_1 x_{t-1-} \varphi_2 x_{t-2} - \ldots - \varphi_p x_{t-p} = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q}$$

Define a backward shift operator as $Bx_t = x_{t-1}$. Then, the above equation can be expressed as:

$\varphi_p\ (B) x_t = \theta_q\ (B) e_t$, where $\varphi_p\ (B)$ and $\theta_q\ (B)$ are the p^{th}-degree polynomial in B defined as, for example,

$$\theta_q\ (B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$$

This is an auto-regressive-moving-average model (ARMA (*p*,*q*) model) which can be employed to model de-trended time series. If the time series is a non-stationary one, then successive first differences of x_t is needed to de-trend it. For *d* such first differences employed in an ARMA model, Box and Jenkins (1970) suggest the term "auto regressive integrated moving average" ARIMA. It is symbolized as follows:

ARIMA (*p*,*d*,*q*) = $\varphi_p\ (B) \delta^d x_t = \theta_q\ (B) e_t$

If seasonal elements are present in x_t, they can be removed by the following conceptualization:

$$\varphi_p\ (B) \delta^d \delta_s x_t = \theta_q\ (B) e_t.$$

Thus, for quarterly data we would have $\delta_4 x_t$.

<u>Intervention Analysis</u>
Intervention analysis involves utilizing indicator variables in the ARIMA model. Since a catastrophic event such as flooding could have two different effects: a temporary or pulse effect that disappears and a permanent or step effect, we represent them in ARIMA as follows:

Pulse effect: $x_t^p = 1$ in the times of intervention, and 0 in other periods;
Step effect: $x_t^s = 1$ in the time periods in which the event occurs and all subsequent periods, and 0 at all time periods before the event.

In general, the following equation is used to determine the intervention effects:

$$v_{k,l}(B) = \frac{\omega_k(B) B^d}{\alpha_l(B)}.$$

Where, $\omega_k(B)$ = ω_k(B) = $\omega_0 + \omega_1^B + \omega_2 B^2 + \ldots + \omega_k B^k$, which contain the direct effects of *x* on *y* over time,

$\alpha_l(B) = \alpha_0 + \alpha_1 B + \alpha_2 B^2 + \ldots + \alpha_l B^l$, and B^d = the dead time (Box and Tiao, 1975).

ARIMA Model for Net Migration (*M*)

The first step in model identification is to check whether the time series is stationary: in a stationary process the mean, variance, and autocorrelation are constant in time. Table A1 shows the results of the unit root tests, the Augmented Dickey-Fuller (ADF) test.

Table A1: ADF Test for Stationary Time Series: H_0 (Series is non-stationary)

County	**Ho (Decision)**	***t* Statistic**	**p**
Hancock	Accept	3.65	.42
Henderson	Accept	2.56	.63
Des Moines	Accept	3.58	.43
Henry	Accept	4.08	.34
Lee	Accept	3.31	.48
Louisa	Accept	2.56	.63

Note: Critical value for $t = 7.86$

Since *M* is non-stationary, we utilize $d = 1$ and re-ran ADF. Table A2 shows the results of this exercise.

Table A2: ADF Test for Stationary Time Series: H_0 (Series is non-stationary); First-Difference Model

County	**Ho (Decision)**	***t* Statistic**	**p**
Hancock	Reject	236.7	.000
Henderson	Reject	16.67	.003
Des Moines	Reject	13.28	.007
Henry	Reject	19.12	.001
Lee	Reject	12.99	.007
Louisa	Reject	12.51	.009

Note: Critical value for $t = 7.86$

Now that the *M* is stationary, we assessed autocorrelation functions (ACF) and partial auto correlation functions (PACF) to determine *p*, and *q*. These statistics can help identify the type of time series for a given data set. Figure A1 shows the ACFs and PACFs for each of the six counties.

Figure A1: ACF's and PACFs: Original Series

ACFs:

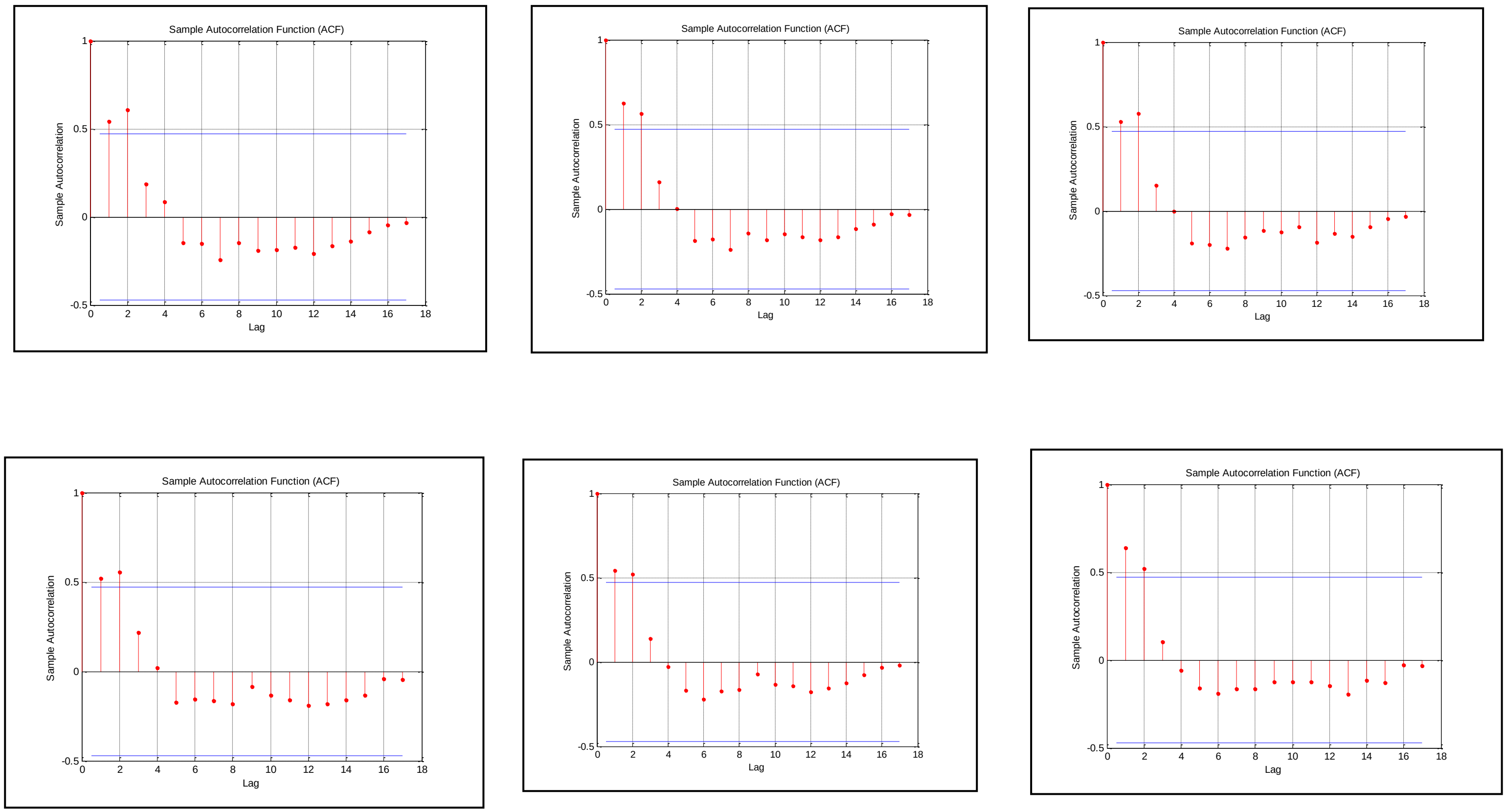
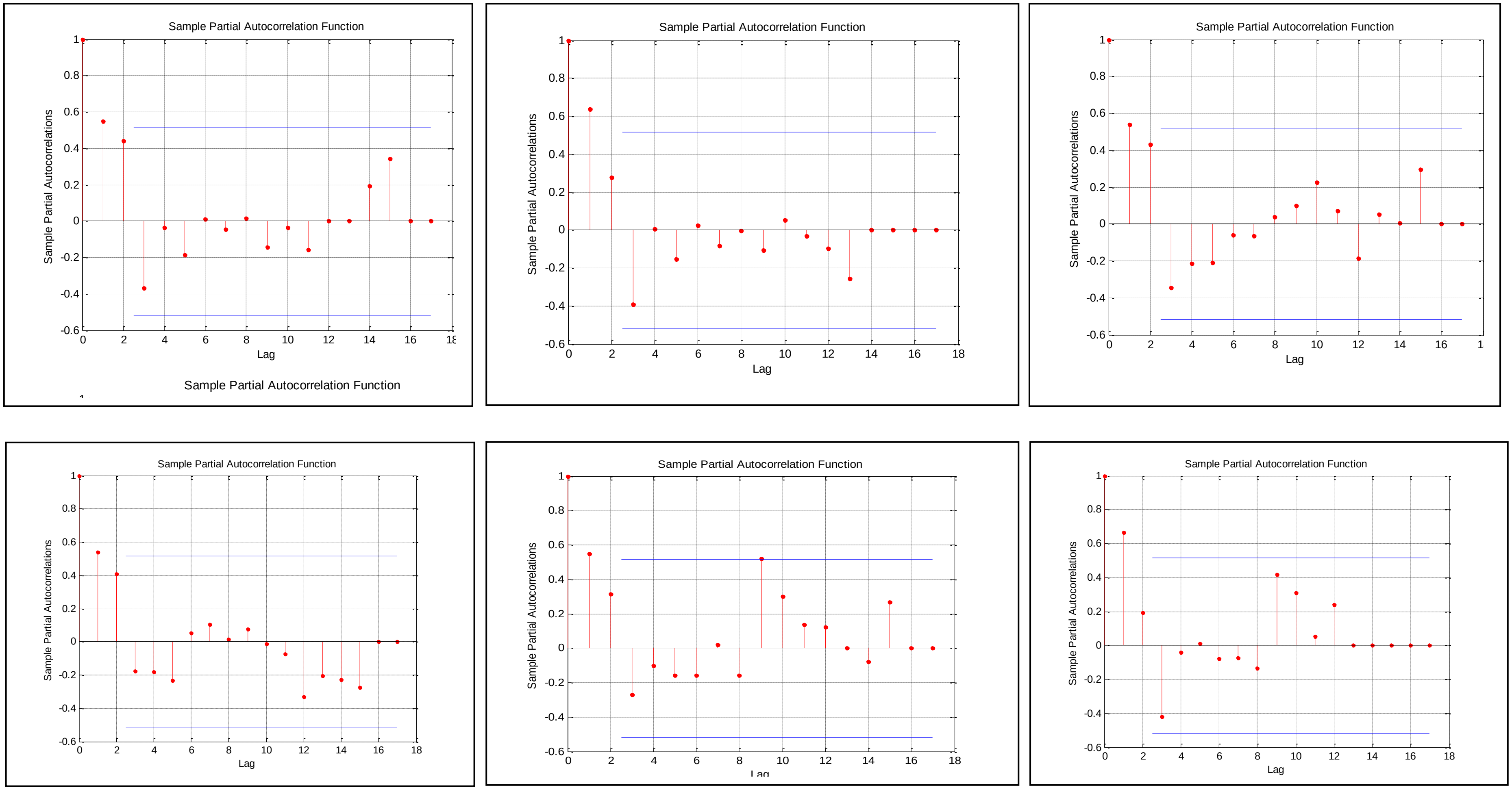


Figure A1 Cont'd ….

PACFs



To identify, p and q, Box and Jenkins (1976) posit that the autoregressive processes be examined. To determine the order of the process, we count the number of spikes in the PACF, which has a cutoff pattern. For a moving-average process, ACF cuts off at a point equal to the order of the MA process; the PACF doesn't provide any additional information, it must die out. Finally, the mixed ARMA model requires a blend of data mining and theory to determine the p, q order.

Based on these heuristics, we examined the following p, q orders for the county M series: p =1, and q = 1, 2 and 3; the ACFs for the counties suggest a strong MA process. In addition, theoretically it is reasonable to assume $q \geq 2$ given that the predictors are lagged dependent variables.

<u>ARIMA Models for the Employment Series (*E*)</u>

Table A3 shows the results of the unit root tests, the ADF test, used to determine stationary time series. Other than Hancock, and Lee, the E series are stationary.

Table A3: ADF Test for Stationary Time Series: H_0 (*Series is non-stationary)

County	**Ho (Decision)**	***t* Statistic**	**p**
Hancock	Reject	15.4942	0.0000
Henderson	Accept*	5.3636	0.1062
Des Moines	Accept*	5.1286	0.1241
Henry	Accept*	1.1493	0.9454
Lee	Reject	6.9879	0.0340
Louisa	Accept*	5.3583	0.1066

Note: Critical value for t = 6.44

For non-stationary data, we utilize d = 1 and re-ran ADF. Table A4 shows the results of this exercise.

Table A4: ADF Test for Stationary Time Series: H_0 (Series is non-stationary); First-Difference Model

County	**Ho (Decision)**	***t* Statistic**	**P**
Hancock	Accept	5.4	>.05
Lee	Accept	3.4	>.05

Note: Critical value for t = 6.44

Next, we assessed the autocorrelation functions (ACF) and partial auto correlation functions (PACF) to determine p, and q. Figure A2 shows the ACFs and PACFs for each of the six counties.

Figure A2: ACF's and PACFs: Original Series

ACFs:

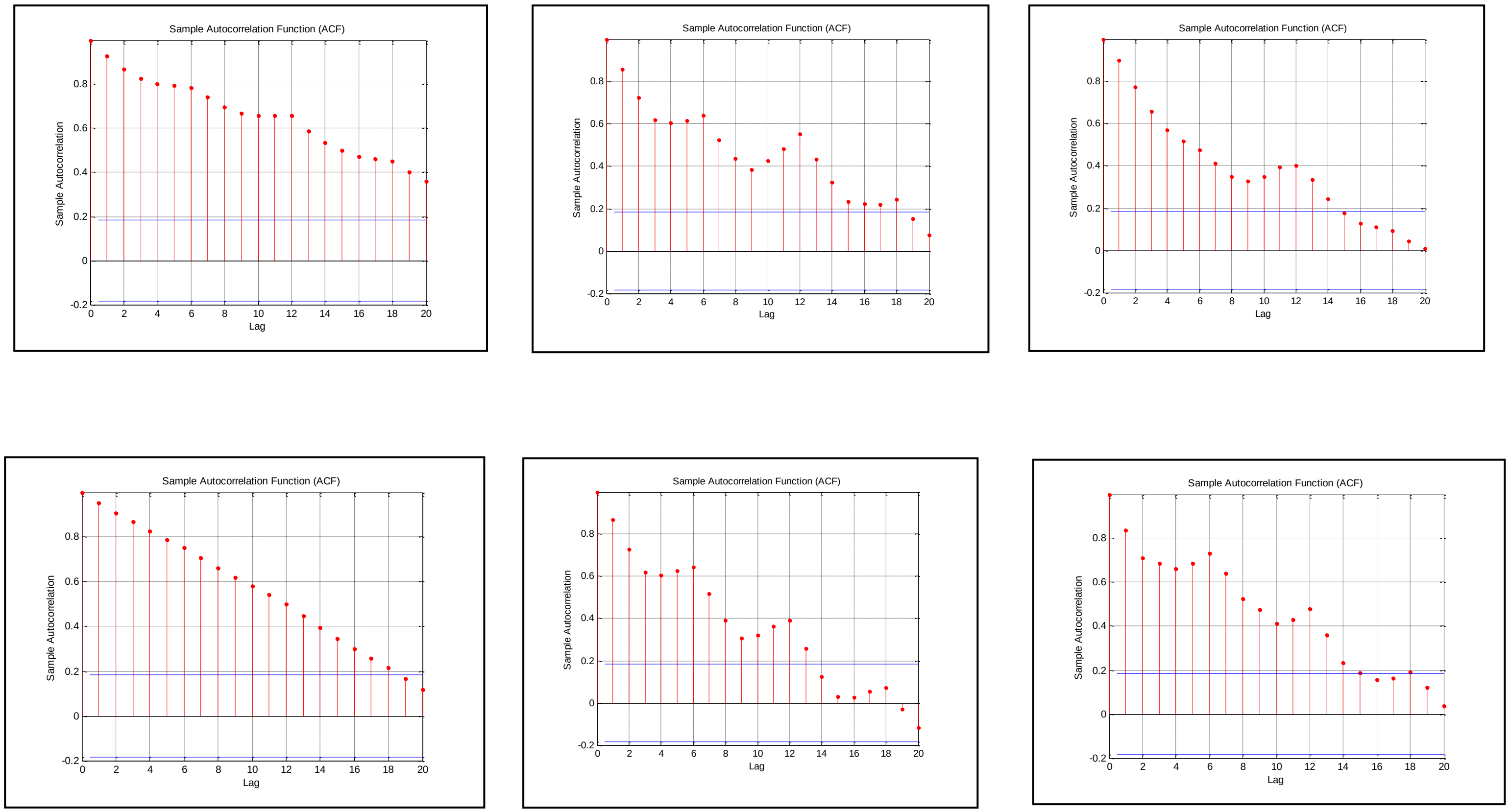
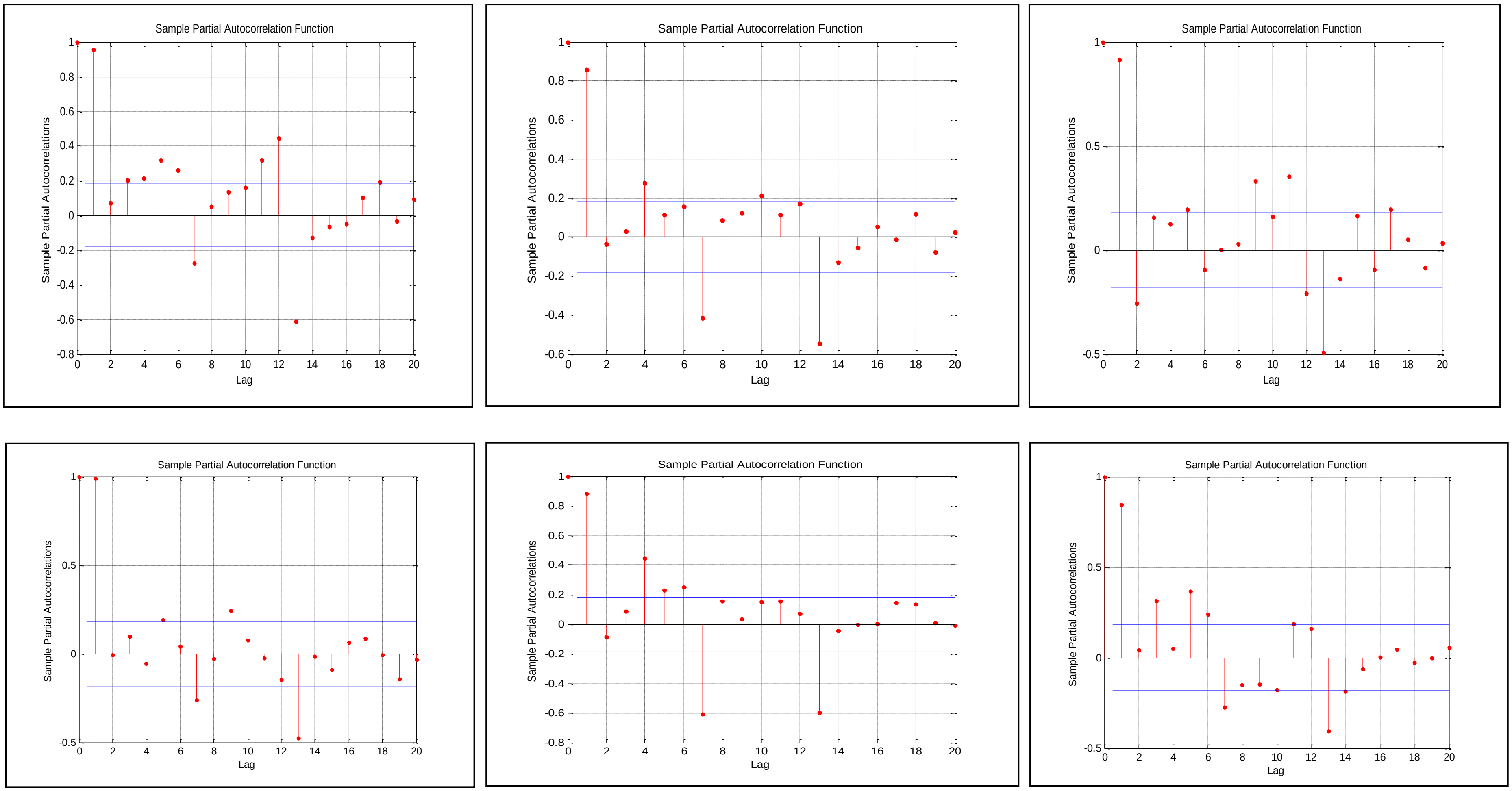


Figure A2 Cont'd ….

PACFs



Appendix 4: Results of Deflated-Model Estimation ($\frac{C}{\sqrt{N}} = \alpha\sqrt{N} + \frac{\beta Y}{\sqrt{N}} + \frac{U}{\sqrt{N}}$)

Hancock, IL:

(i) Analysis of Variance Table

	DF	SS	MS	F- Statistic	P- Value
α	1	$3.367381289687417 \times 10^{8}$	$3.367381289687417 \times 10^{8}$	7022.535407223228	$1.085160930452062 \times 10^{-23}$
β	1	2718730.631015837	2718730.631015837	56.69801093651425	$8.243097722374861 \times 10^{-7}$
D_1	1	128908.88853400946	128908.88853400946	2.6883419374225563	0.11945698845750304
Error	17	815168.291865138	47951.07599206694		
Total	20	$3.404009367801566 \times 10^{8}$			

(ii) Parameter Estimates (Adjusted R2 = .997183); (DW = .847853).

	Estimate	Standard Error	t- Statistic	P- Value
α	−0.322433285967678	3.8333897432785538	−0.0841117933633101	0.9339501153616654
β	0.9526300269756479	0.1255872048362721	7.585406715736613	$7.474722333779655 \times 10^{-7}$
D_1	267.95590947583645	163.42597546713665	1.6396163994732877	0.1194569884575547

Henderson, IL

(i) Analysis of Variance Table

	DF	SS	MS	F- Statistic	P- Value
α	1	$1.299164749677049 \times 10^{8}$	$1.299164749677049 \times 10^{8}$	5477.569210646359	$8.918963364750896 \times 10^{-23}$
β	1	1627086.192952275	1627086.192952275	68.60159372241804	$2.267868376938071 \times 10^{-7}$
D_1	1	91697.4587559551	91697.4587559551	3.8661699903802997	0.06581590745949886
Error	17	403204.4123072556	23717.906606309152		
Total	20	$1.320384630317203 \times 10^{8}$			

(ii) Parameter Estimates (Adjusted R2 = .996407); (DW = .80207)

	Estimate	Standard Error	t- Statistic	P- Value
α	−1.900154341435329	3.609626432412734	−0.5264130172509942	0.6054020798382294
β	1.014868315275673	0.12232116532878183	8.296751527406167	$2.215086465467384 \times 10^{-7}$
D_1	227.84156467927806	115.87572961463998	1.9662578646710163	0.06581590745948855

Des Moines, IA

(i) Analysis of Variance Table

	DF	SS	MS	F- Statistic	P- Value
α	1	$5.229815867875407 \times 10^{8}$	$5.229815867875407 \times 10^{8}$	6768.415193383354	$1.483324302447347 \times 10^{-23}$
β	1	$1.979868045788657 \times 10^{7}$	$1.979868045788657 \times 10^{7}$	256.23404916269243	$1.099123556993179 \times 10^{-11}$
D_1	1	305551.4535706043	305551.4535706043	3.954439607350467	0.06309269537384249
Error	17	1313555.200348749	77267.95296169115		
Total	20	$5.443993738993466 \times 10^{8}$			

(ii) Parameter Estimates (Adjusted R2 = .997161); (DW = .885517)

	Estimate	Standard Error	t- Statistic	P- Value
α	−63921.25974376504	79434.8495323562	−0.8047004572939739	0.4321032042895888
β	0.9635808875114265	0.05974018203835303	16.129527139586052	$9.731490069576806 \times 10^{-12}$
D_1	414.359177995949	208.36966292501333	1.9885772822172572	0.06309269537383937

Henry, IA

(i) Analysis of Variance Table

	DF	SS	MS	F- Statistic	P- Value
α	1	$2.208741731810762 \times 10^{8}$	$2.208741731810762 \times 10^{8}$	5799.769869273905	$5.494409242735438 \times 10^{-23}$
β	1	9193749.940104723	9193749.940104723	241.4118098114812	$1.768779540254269 \times 10^{-11}$
D_1	1	152789.788410753	152789.788410753	4.01199288443264	0.06138781665133293
Error	17	647415.5059101305	38083.265053537085		
Total	20	$2.308681284155018 \times 10^{8}$			

(ii) Parameter Estimates (Adjusted R2 = .996701); (DW = .842455)

	Estimate	Standard Error	t- Statistic	P- Value
α	−1.5571329468936597	1.8611557692565883	−0.836648373346866	0.4143967792955172
β	0.9892109898055139	0.06315479492558533	15.66327609758042	$1.555256608325602 \times 10^{-11}$
D_1	294.0525938316997	146.8063826327813	2.0029959771383874	0.06138781665133534

Lee, IA

(i) Analysis of Variance Table

	DF	SS	MS	F- Statistic	P- Value
α	1	$4.183805985512396 \times 10^{8}$	$4.183805985512396 \times 10^{8}$	5335.597095069148	$1.114211586213328 \times 10^{-22}$
β	1	$1.711620115430492 \times 10^{7}$	$1.711620115430492 \times 10^{7}$	218.2824764670435	$3.936933247434426 \times 10^{-11}$
D_1	1	323871.3790463805	323871.3790463805	4.130323430865952	0.058048181878210245
Error	17	1333022.349446889	78413.07937922879		
Total	20	$4.371536934340378 \times 10^{8}$			

(ii) Parameter Estimates (Adjusted R2 = .996413); (DW = .839751)

	Estimate	Standard Error	t- Statistic	P- Value
α	−1.4484288212050773	1.8801095489398183	−0.7703959708208689	0.45163927319140884
β	0.9903494944218788	0.06686558082670417	14.811050501282148	$3.785375782368306 \times 10^{-11}$
D_1	425.96284369171025	209.59440593554766	2.032319716694624	0.05804818187821677

Louisa, IA

(i) Analysis of Variance Table

	DF	SS	MS	F- Statistic	P- Value
α	1	$1.209149047003771 \times 10^{8}$	$1.209149047003771 \times 10^{8}$	12191.382385420398	$1.006526198650006 \times 10^{-25}$
β	1	6873922.823296681	6873922.823296681	693.0710637728108	$3.21948158266463 \times 10^{-15}$
D_1	1	24522.712342470884	24522.712342470884	2.472530280990235	0.1342766214982093
Error	17	168607.07956832155	9918.063504018915		
Total	20	$1.279819573155846 \times 10^{8}$			

(ii) Parameter Estimates (Adjusted R2 = .99845); (DW = .795168)

""	Estimate	Standard Error	t- Statistic	P- Value
α	−1.4036290395828892	1.1199824638476479	−1.2532598365520713	0.22707481291293097
β	0.9816404952353436	0.03722219741766347	26.372448789643855	$3.127032295823643 \times 10^{-15}$
D_1	117.57452967512924	74.77259283097636	1.5724281481171418	0.13427662149814534

Appendix 5: Economic Impacts: County-wise Details

Henderson, IL:

	Direct Requirement: Point and Interval Estimates			Total Requirement: Point and Interval Estimates		
	Point	**Best**	**Worst**	**Point**	**Best**	**Worst**
Agriculture, forestry, fishing & hunting	-0.884653	-0.142424	1.91104	-1.14424	-0.184217	2.47181
Mining	-2.33314	-0.375624	5.04008	-2.37065	-0.381663	5.12111
Utilities	-0.823042	-0.132505	1.77794	-1.65146	-0.265876	3.5675
Construction	-0.446446	-0.0718755	0.964417	-0.446446	-0.0718755	0.964417
Manufacturing	-8.80219	-1.41711	19.0146	-15.0596	-2.42451	32.5318
Wholesale trade	-1.36188	-0.219255	2.94194	-2.90548	-0.467767	6.27644
Retail trade	-0.125426	-0.020193	0.270947	-3.90066	-0.627987	8.42625
Transportation & warehouse	-1.30684	-0.210395	2.82305	-2.13876	-0.344329	4.62017
Information	-1.14766	-0.184767	2.47918	-3.05984	-0.492619	6.6099
Finance, insurance, real estate & leasing	-7.02267	-1.13061	15.1704	-16.3148	-2.6266	35.2434
Professional services	-6.16912	-0.993197	13.3266	-6.57914	-1.05921	14.2123
Educational services	-0.174276	-0.0280576	0.376474	-7.75136	-1.24793	16.7446
Arts & entertainment	-0.65348	-0.105207	1.41165	-3.67138	-0.591072	7.93094
Other services	-0.554535	-0.0892772	1.19791	-2.49644	-0.401914	5.39283
Government	-0.237669	-0.0382634	0.513414	-1.08788	-0.175144	2.35006
Total Impact				-70.578	-11.363	152.464

Des Moines:

	Direct Requirement: Point and Interval Estimates			Total Requirement: Point and Interval Estimates		
	Point	**Best**	**Worst**	**Point**	**Best**	**Worst**
Agriculture, forestry, fishing & hunting	-3.9242	-1.6417	-6.20693	-5.07571	-2.12344	-8.02828
Mining	-10.3495	-4.32975	-16.3699	-10.5159	-4.39936	-16.6331
Utilities	-3.6509	-1.52737	-5.77465	-7.32565	-3.06471	-11.587
Construction	-1.98037	-0.828496	-3.13237	-1.98037	-0.828497	-3.13237
Manufacturing	-39.0453	-16.3348	-61.7582	-66.8022	-27.9469	-105.661
Wholesale trade	-6.04109	-2.52731	-9.55523	-12.8883	-5.39187	-20.3855
Retail trade	-0.556373	-0.232761	-0.880019	-17.3028	-7.23869	-27.368
Transportation & warehouse	-5.79697	-2.42518	-9.1691	-9.48725	-3.96902	-15.006
Information	-5.09085	-2.12977	-8.05223	-13.573	-5.67833	-21.4686
Finance, insurance, real estate & leasing	-31.1516	-13.0324	-49.2727	-72.3702	-30.2763	-114.468
Professional services	-27.3654	-11.4484	-43.284	-29.1842	-12.2093	-46.1607
Educational services	-0.773067	-0.323415	-1.22276	-34.384	-14.3847	-54.3853
Arts & entertainment	-2.89875	-1.2127	-4.58497	-16.2857	-6.81319	-25.7592
Other services	-2.45984	-1.02908	-3.89075	-11.0739	-4.63279	-17.5156
Government	-1.05427	-0.441056	-1.66754	-4.82571	-2.01885	-7.63285
Total Impact				-313.07	-130.98	-495.19

Henry:

	Direct Requirement: Point and Interval Estimates			Total Requirement: Point and Interval Estimates		
	Point	**Best**	**Worst**	**Point**	**Best**	**Worst**
Agriculture, forestry, fishing & hunting	-2.09005	1.35407	-5.53441	-2.70335	1.75141	-7.15842
Mining	-5.5122	3.57117	-14.5962	-5.60082	3.62859	-14.8309
Utilities	-1.94449	1.25977	-5.14897	-3.90168	2.52777	-10.3316
Construction	-1.05476	0.683343	-2.79298	-1.05476	0.683343	-2.79298
Manufacturing	-20.7958	13.4729	-55.0667	-35.5792	23.0506	-94.2129
Wholesale trade	-3.21752	2.08453	-8.51992	-6.86438	4.44721	-18.1767
Retail trade	-0.296327	0.191981	-0.784668	-9.21558	5.97047	-24.4026
Transportation & warehouse	-3.0875	2.00029	-8.17563	-5.05296	3.27365	-13.3801
Information	-2.71141	1.75664	-7.17977	-7.22908	4.68348	-19.1424
Finance, insurance, real estate & leasing	-16.5915	10.7491	-43.934	-38.5448	24.9719	-102.066
Professional services	-14.575	9.44264	-38.5942	-15.5436	10.0702	-41.1592
Educational services	-0.41174	0.266753	-1.09028	-18.3131	11.8644	-48.4927
Arts & entertainment	-1.54389	1.00023	-4.08818	-8.67386	5.61951	-22.9682
Other services	-1.31013	0.848787	-3.46918	-5.898	3.82112	-15.6178
Government	-0.561508	0.363782	-1.48686	-2.5702	1.66515	-6.80583
Total Impact				-166.75	108.029	-441.54

Lee:

	Direct Requirement: Point and Interval Estimates			Total Requirement: Point and Interval Estimates		
	Point	**Best**	**Worst**	**Point**	**Best**	**Worst**
Agriculture, forestry, fishing & hunting	-3.95292	-2.86007	-5.04391	-5.11286	-3.69933	-6.52399
Mining	-10.4252	-7.54301	-13.3026	-10.5929	-7.66429	-13.5164
Utilities	-3.67762	-2.66088	-4.69263	-7.37926	-5.33914	-9.41591
Construction	-1.99487	-1.44335	-2.54544	-1.99487	-1.44335	-2.54544
Manufacturing	-39.3311	-28.4574	-50.1863	-67.291	-48.6873	-85.8632
Wholesale trade	-6.0853	-4.40292	-7.76483	-12.9826	-9.39337	-16.5658
Retail trade	-0.560445	-0.405501	-0.715126	-17.4294	-12.6108	-22.2399
Transportation & warehouse	-5.83939	-4.225	-7.45105	-9.55667	-6.91458	-12.1943
Information	-5.1281	-3.71036	-6.54345	-13.6724	-9.89242	-17.4459
Finance, insurance, real estate & leasing	-31.3796	-22.7042	-40.0403	-72.8998	-52.7455	-93.02
Professional services	-27.5656	-19.9447	-35.1737	-29.3977	-21.2702	-37.5114
Educational services	-0.778724	-0.563433	-0.99365	-34.6356	-25.06	-44.1949
Arts & entertainment	-2.91996	-2.11269	-3.72586	-16.4049	-11.8695	-20.9326
Other services	-2.47784	-1.7928	-3.16172	-11.1549	-8.07095	-14.2336
Government	-1.06198	-0.768379	-1.35508	-4.86102	-3.51711	-6.20265
Total Impact				-315.37	-228.18	-402.41