Table of Contents

FEDERAL RESERVE BANK of KANSAS CITY

Financial Vulnerability and Personal Finance Outcomes of Natural Disasters

Mid-Continent Regional Science Association Annual Conference

Oregon, OH

June 9, 2017

Kelly D. Edmiston†

Sr. Economist

†This presentation and the associated paper represent the views of the speaker/author and not necessarily those of the Federal Reserve Bank of Kansas City or the Federal Reserve System.

Foundations: Economic Impact

- Losses
  - Direct—damage to or destruction of physical assets such as homes, businesses and business inventories, automobiles, and public infrastructure, as well as loss of life
  - Indirect
    - Loss of business revenue and increased business costs, unemployment, and reductions in tourism; fiscal impact of these losses
    - No consensus "rule of thumb" to estimate indirect losses from direct losses, which are often tallied
- Gains
  - Economic activity around reconstruction
  - Improved infrastructure
  - But a large share of the remuneration could be transferred outside of the affected area (analysis of 1979 Hurricane Frederick in Alabama estimated a 71 percent leak without having been turned over once)
- General consensus of this literature is that natural disasters, particularly in areas receiving a "direct hit," reduce economic activity, typically measured by employment, in the immediate period, but may increase economic activity in later periods

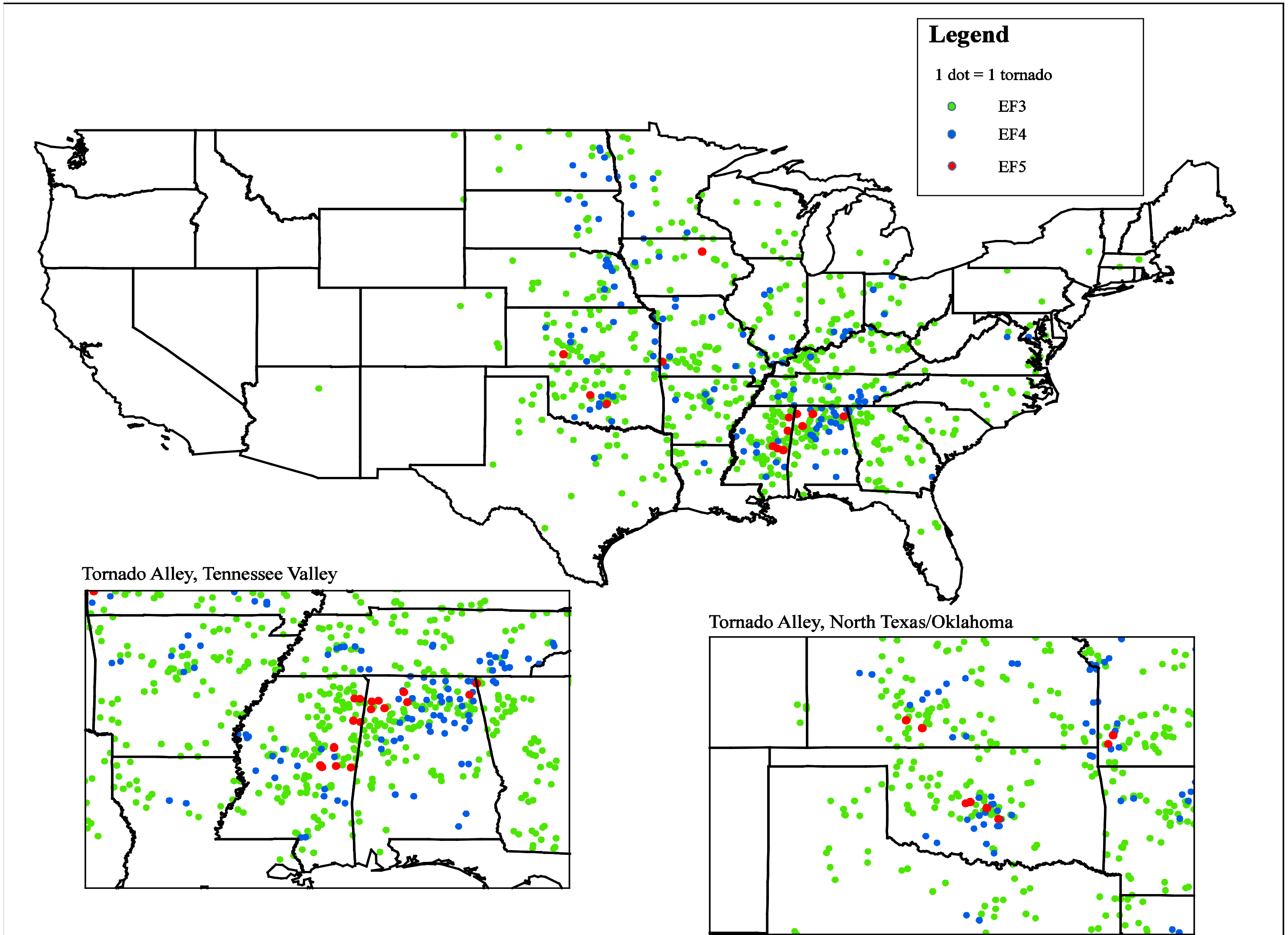
Foundations: "Hazards are natural . . . but disasters are not" (Cannon, 2004)

- **Natural hazards do not need to be as disastrous as they are**
- In many cases, human activities have created the conditions for <u>disaster</u>
  - Analogous to "death by natural causes"
- Factors in vulnerability (Enarson, 2012; referring to women specifically)
  - Poverty
  - Physical challenges
  - Racial or ethnic marginalization
  - Insecure housing
  - Language barriers
  - Violence
- Does <u>financial</u> vulnerability matter?

Why Hurricanes?

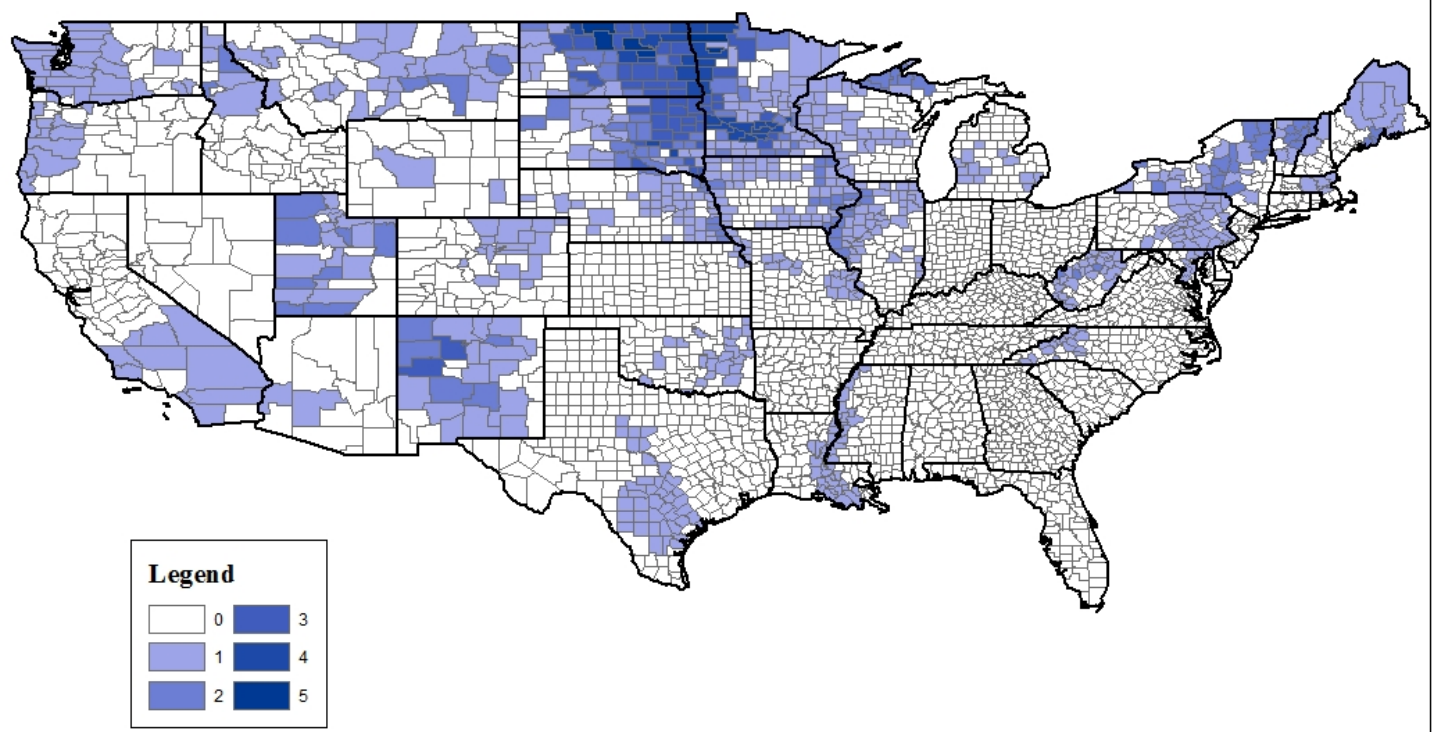
- Good data are available from quality source
- Can be tracked through census tracts at specific times and with good precision
  - Tornados can be identified geographically, but not the path, or with any precision, intensity
  - Earthquakes, floods, and wildfire require using disaster declarations at the county level
  - Earthquake intensity varies by geological formations, etc.
- Hurricanes only a threat for coastal states
  - Limits analysis
  - Do not need to account for probability of event occurring (or not as important to do so)
- Limited number of events

Incidences of Tornadic Activity at EF-3 and Above, 2000-2014



Source: Federal Emergency Management Agency

“Emergency” Disaster Declarations for Floods over the Study Period



Source: Federal Emergency Management Agency

Exogeneity

- Natural disasters are purely exogenous events in that they cannot be controlled or precisely predicted
  - U.S. Geological Survey: "Neither the USGS nor any other scientists have ever predicted a major earthquake. They do not know how, and they do not expect to know how any time in the foreseeable future." (http://www.usgs.gov/faq/categories/9830/3278)
- But . . . can probably assign a probability of a natural disaster occurring using climatic, geological, and other relevant information; e.g.,
  - proximity to a major seismic fault line
  - previous history of tornados ("tornado alleys")

Exogeneity: Relative Risk

- If the risk of a hurricane is substantially different in some census tracts than others, we might expect that residents in the more-prone areas might better prepare, for example, by outfitting their homes with hurricane strips
  - FEMA (2012): 46 percent of survey respondents "familiar" with local hazards (did not control for exposure to known hazards)
- Relative risk can provide some insight into this phenomenon for this specific case.
- Goal is to see the probability of event occurring in an "exposed" area relative to the probability of an event occurring in an unexposed area

Exogeneity: Relative Risk

- Exposure here is incidence of a "storm" events measuring category 9-12 on the Beaufort Wind Force Scale
  - 0 = calm
  - 2 = light breeze
  - 9 = strong/severe gale, 47-54 mph
  - 10 = storm
  - 11 = violent storm
  - 12 = hurricane force, ≥ 73mph

Relative Risk

		Hurricane Strikes +	Hurricane Strikes -
Storm Exposure	+	809	1,407
	-	4,206	11,393

$$RR = \frac{809}{809+1{,}407} \bigg/ \frac{4{,}206}{4{,}206+11{,}393} = \frac{0.36507}{0.26963} = 1.35$$

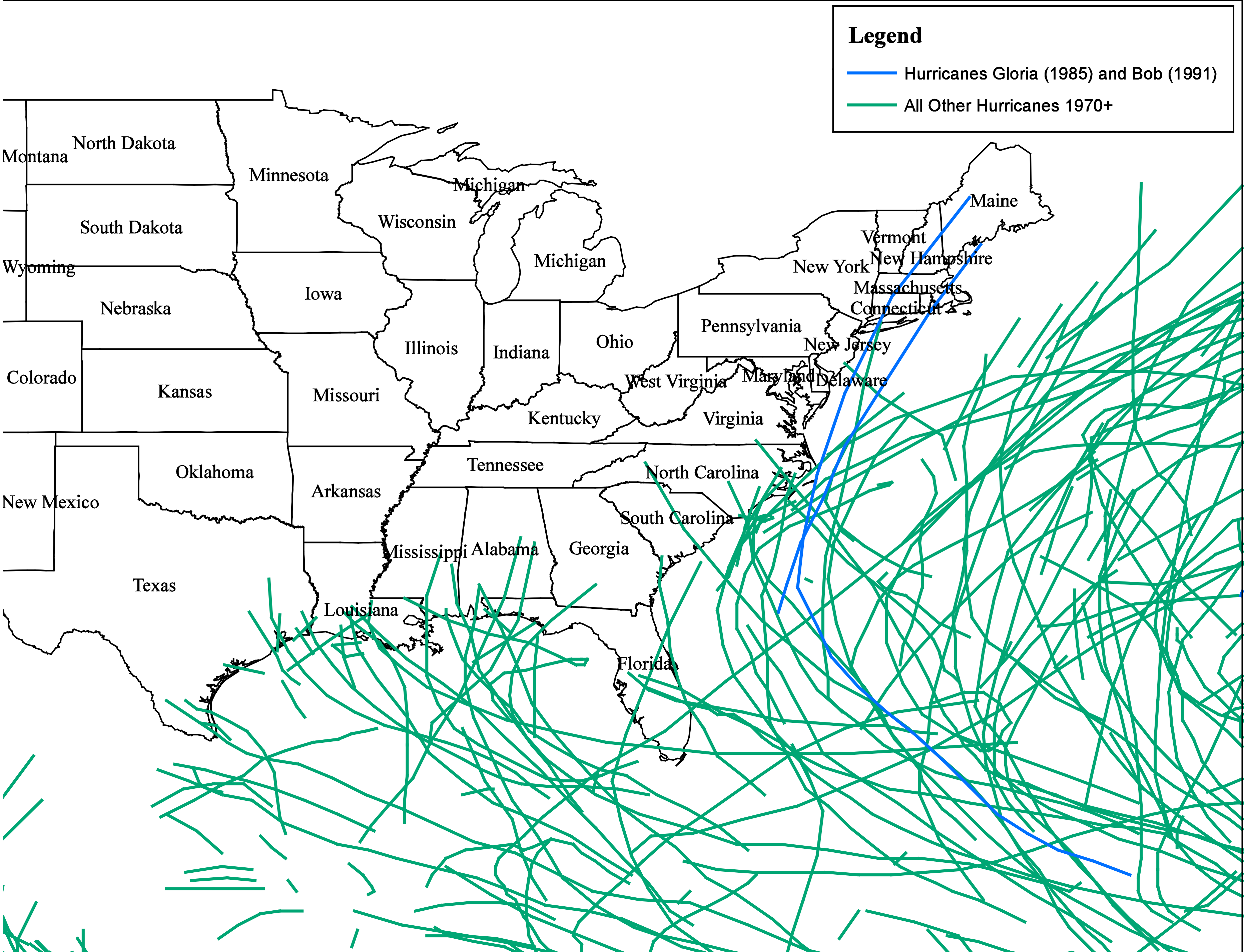
$$\log RR \sim N$$

$$se = \sqrt{\left[\frac{1}{809}+\frac{1}{4{,}206}\right]-\left[\frac{1}{809+1{,}407}+\frac{1}{4{,}206+11{,}373}\right]} = 0.0310$$

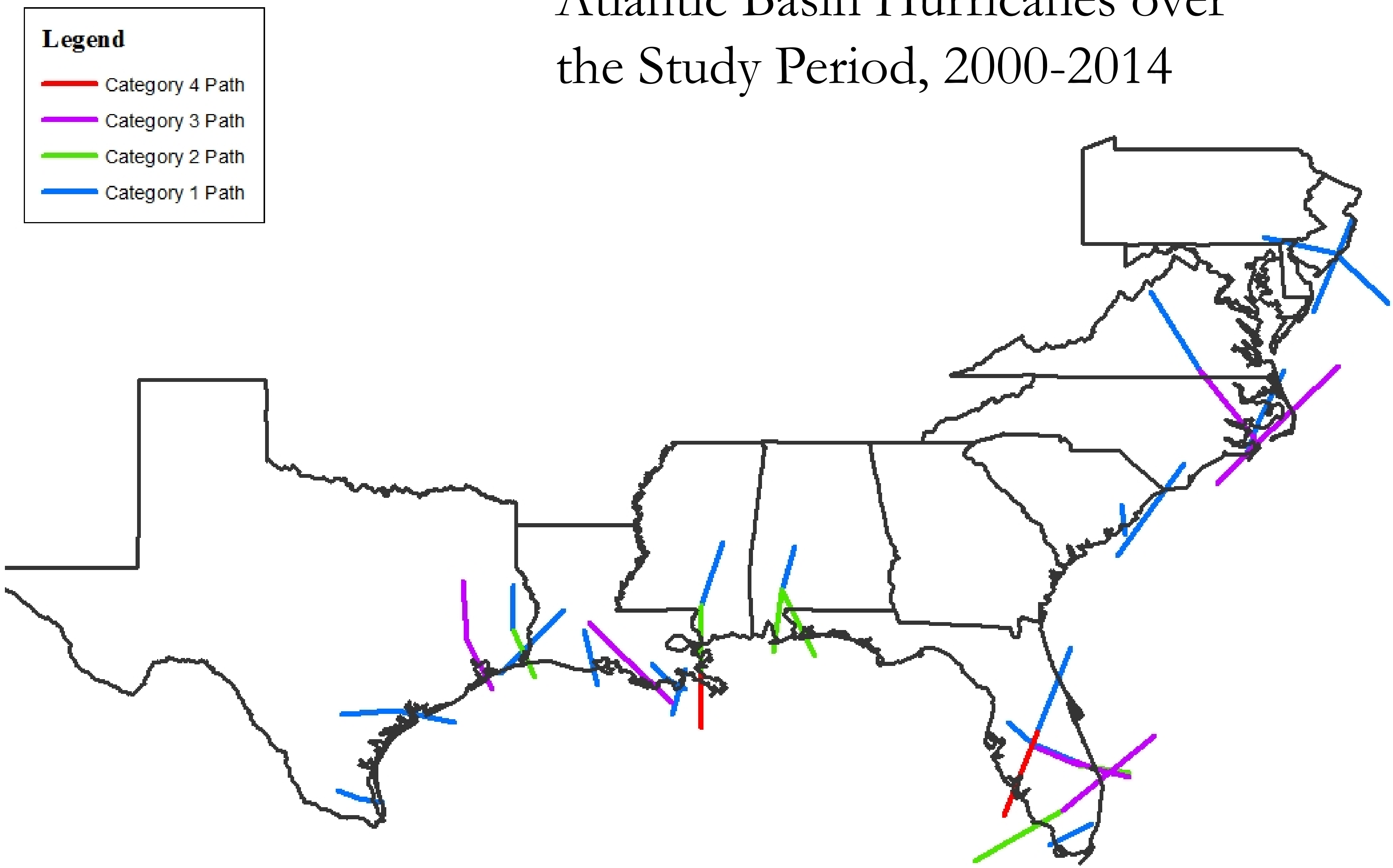
$$Z = \frac{\log RR}{\sigma} = \frac{0.1316}{0.0310} = 4.25$$

Exogeneity

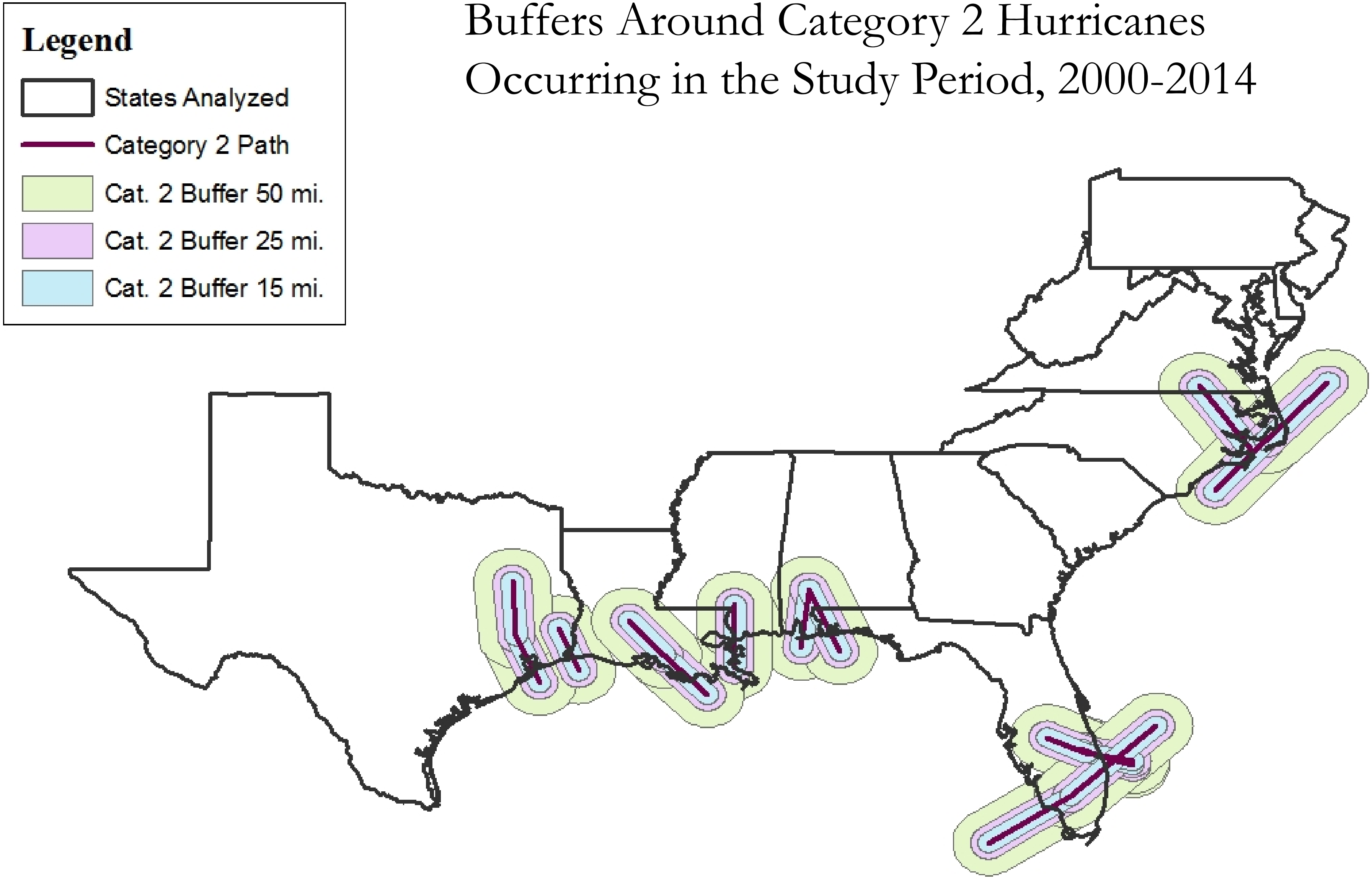
- Still, perceptions of risks by most are overly optimistic
  - Rethans (1979): an "overwhelming majority" of respondents to a random, stratified national survey reported that their fatality risk associated with traffic accidents was below normal
  - Viscusi and Zeckhauser (2006) evaluated perceptions of fatality risk for tornados, hurricanes, and floods (as well as terrorism). They argue that "risk beliefs have many rational components, but fall short of what one would expect with fully rational Bayesian assessments of risk" (p. 34)
  - "The consensus view of research around perceptions of risk from natural hazards is "less a question of predicted physical outcomes than of values, attitudes, social influences, and cultural identity" (Wachinger, Renn, et al., 2010, p. 71)
- Even when vulnerabilities to natural disasters are well-understood, at-risk residents often do not take protective action commensurate with risk (see, e.g., DeBastiani et al., 2015)
- **Control for probability of disaster events by restricting analysis to states with history of hurricanes**


Legend
Hurricanes Gloria (1985) and Bob (1991)
All Other Hurricanes 1970+
Montana
North Dakota
Minnesota
Michigan
Wisconsin
South Dakota
Michigan
Maine
Vermont
New Hampshire
New York
Massachusetts
Connecticut
Wyoming
Nebraska
Iowa
Pennsylvania
Ohio
Illinois
Indiana
New Jersey
Colorado
Kansas
Missouri
West Virginia
Maryland
Delaware
Kentucky
Virginia
Tennessee
North Carolina
Oklahoma
Arkansas
New Mexico
South Carolina
Mississippi
Alabama
Georgia
Texas
Louisiana
Florida

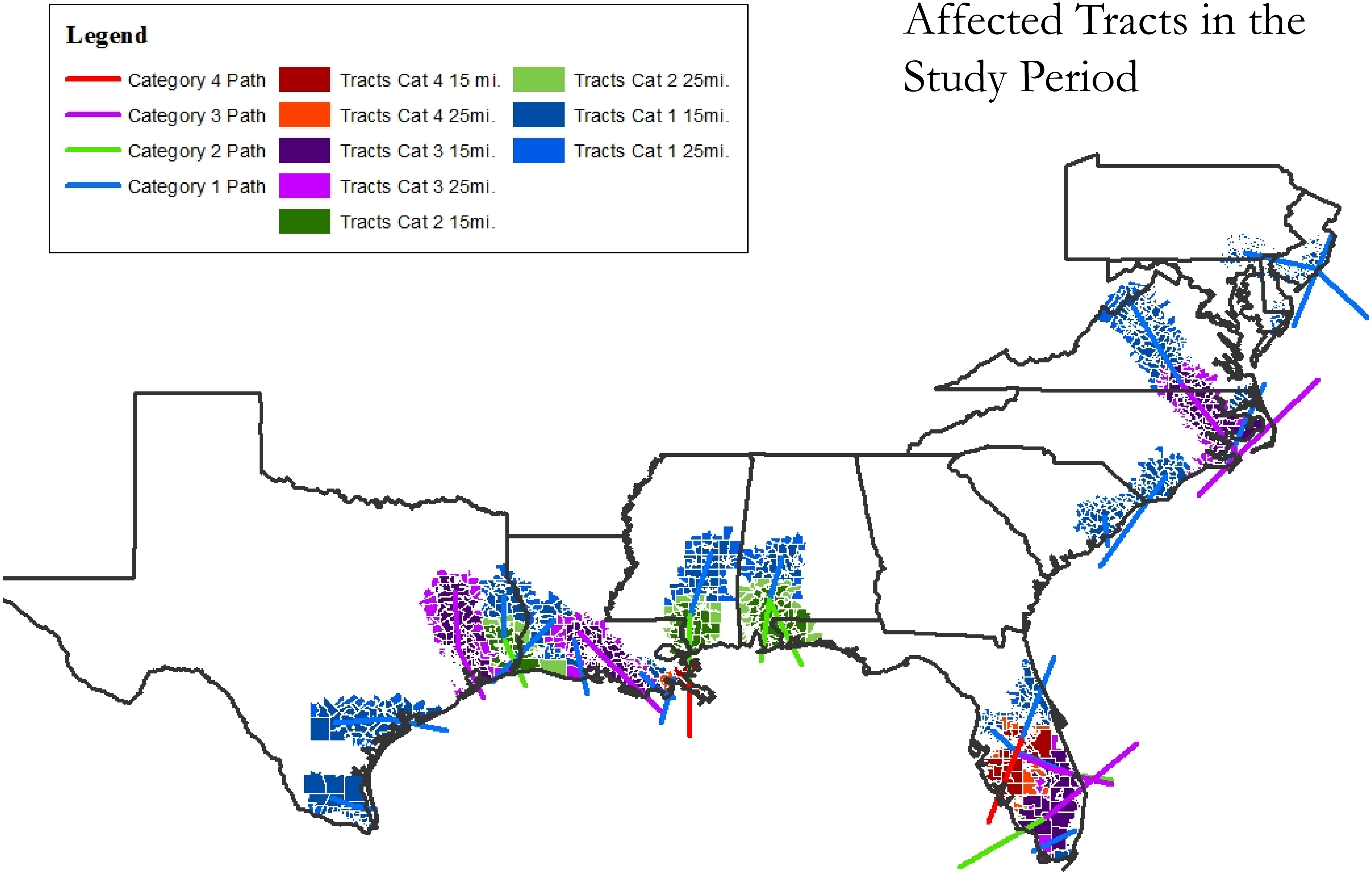
Atlantic Basin Hurricanes over the Study Period, 2000-2014



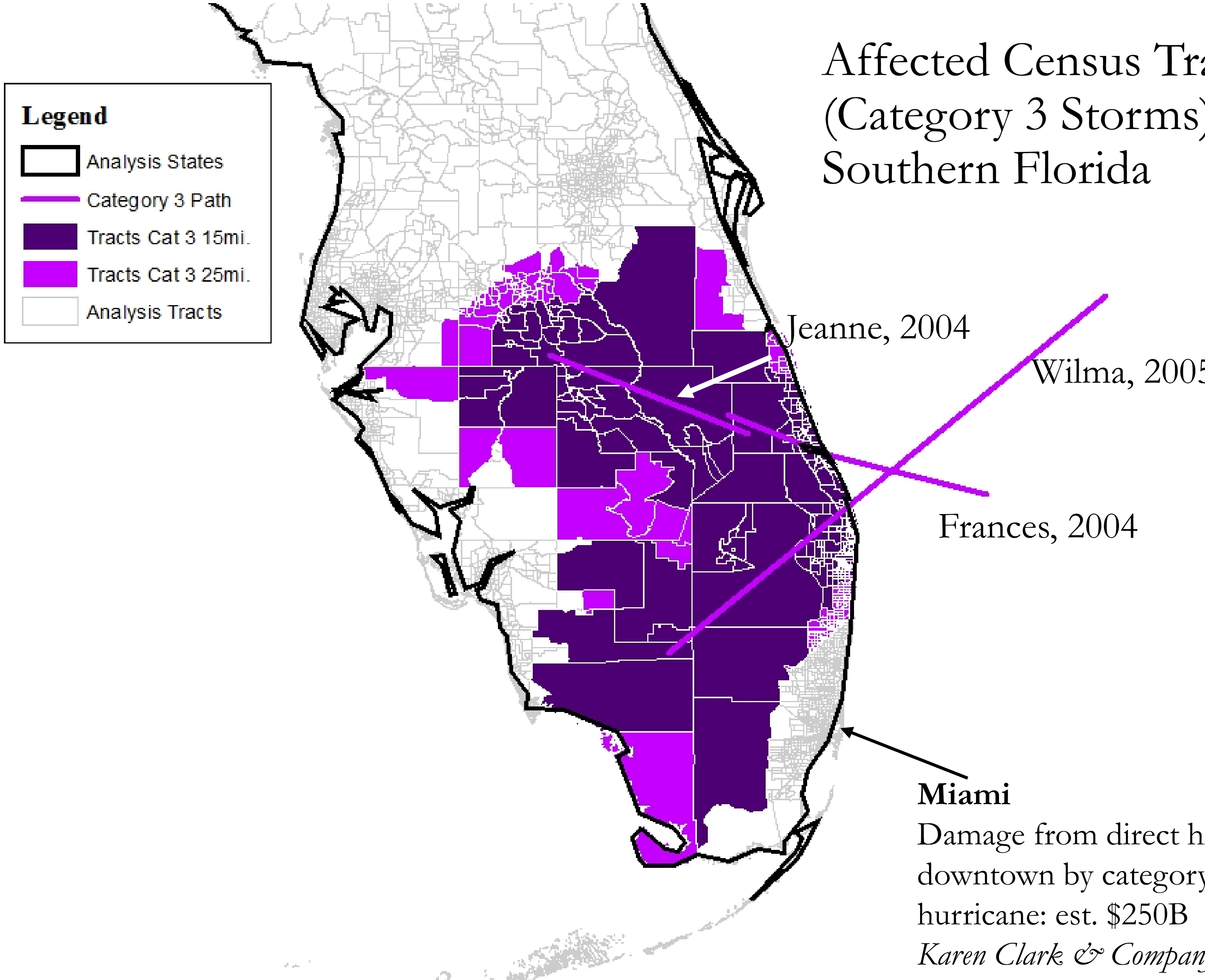
Buffers Around Category 2 Hurricanes Occurring in the Study Period, 2000-2014



Affected Tracts in the Study Period



Affected Census Tracts (Category 3 Storms) Southern Florida



Miami
Damage from direct hit on downtown by category 5 hurricane: est. $250B
Karen Clark & Company (2015)

Related Existing Research

- Gallagher, Justin and Daniel Hartley (2014). "Household Finance After a Natural Disaster: The Case of Hurricane Katrina," *Federal Reserve Bank of Cleveland Working Paper 14-06*, July (updated Dec 2015)
  - Use topology to assess flood depths at census block group level; assign individuals in NY Fed CCP
  - Compare credit outcomes depending on degree of flooding (3 categories)
  - Results
    - Flooding reduces total debt, increasing in the degree of flooding; reduction in debt driven "almost exclusively" by decreased mortgage debt, attributed largely to flood claims having been used to pay off mortgages rather than to rebuild); esp. common if rebuild cost > value pre-Katrina
    - Temporary increase of $700 (23 percent) in credit card debt, presumably used to smooth consumption
    - 90-day delinquency rates increased by ten percent for those in the most flooded areas for a one-year following Katrina, and credit scores were lower for the most-flooded areas for a two-year period following Katrina
- Some other related work, largely on international level

Empirical Model: Aggregation

- Financial decisions generally made at individual or household level, so why not look at individual credit data?
  - Extremely noisy; teasing out the significance of financial vulnerability would almost surely be unsuccessful
  - Can account for "inclusion" in the traditional financial system
  - Computational resources are a binding constraint
  - If our interest is in policy, there may be more value in seeing how the financial vulnerability of a community (like a census tract) affects disaster outcomes

Empirical Model (1)

- Matrix **H** with elements $h_{i,t}^{m,d,j}$
  - Tract *i* at time *t*
  - Intensity: $m \in \{1,\ldots,5\}$
  - Buffer distance (in miles from eye) $d \in D$
  - Lag structure: $l \in \{0,1,\ldots,L\}$
  - $h_{i,t}^{3,25,2} = \mathbf{1}$ if tract *i* fell within a <u>25</u>-mile radius of the eye of a category <u>3</u> hurricane at time t – <u>2</u>
- Basic fixed effects model for outcome *y* (say, credit score)

$$y_{it} = \mu_i + \lambda_t + \mathbf{H}'_{it}\mathbf{a} + \mathbf{X}'_{it}\mathbf{b} + \mathbf{C}'_{it}\boldsymbol{\delta} + u_{it} \quad u \sim IID,\ E(u) = 0$$

- $\mathbf{H}'_{it}, \mathbf{X}'_{it}, \mathbf{C}'_{it}$ are row vectors for tract *i* at time *t*

Empirical Model (2)

$$y_{it} = \mu_i + \lambda_t + \mathbf{H}'_{it}\mathbf{a} + \mathbf{X}'_{it}\mathbf{b} + \mathbf{C}'_{it}\boldsymbol{\delta} + u_{it} \quad u \sim IID,\ E(u) = 0$$

- **C** contains $r = 1, \ldots, R$ credit variables
- **X** contains $k = 1, \ldots, K$ control variables unrelated to credit

- Identification of the effects of financial vulnerability is accomplished by interacting the "treatment" variables, which in this case are hurricane strikes and their lags, with the regressors of interest, which are the RHS credit variables.

Empirical Model (3)

- The model specification is essentially a difference-in-differences specification. Each variable $c_{it}^{r} \in \mathbf{C}$ must be pre-multiplied by the corresponding row vector $\mathbf{H}'_{it} \in \mathbf{H}$

$$y_{it} = \mu_i + \lambda_t + \mathbf{H}'_{it}\mathbf{A} + \mathbf{X}'_{it}\mathbf{B} + \mathbf{C}'_{it}\mathbf{\Gamma} + \mathbf{H}'_{it}\boldsymbol{\delta}\left(c_{it}^{1} + c_{it}^{2} + \cdots + c_{it}^{R}\right) + e_{it} \quad \forall i,t$$

Empirical Model: Fixed Effects

- F-test for significance of fixed effects has little value with thousands of cross-sections (will always reject the null hypothesis of no fixed effects)
- Fixed effects discards between-tract variability, measuring only variability within tracts.
- By discarding this between-tract variability, one may be less likely to get unbiased estimates, but one also loses a great deal of "signal" in the data.
- Fixed effects may absorb virtually all of the variation in the data so that identification "rests on very slim margins" (Fisher, et al., 2012, 3757).
- Fixed effects can actually increase the bias due to omitted variables if the time-varying omitted variables (which could be measurement errors) are more strongly correlated with the treatment than time-invariant omitted variables that have been removed with fixed effects (Fisher, et al., 2012, 3760).

Source: Fisher, Anthony C., W. Michael Hanemann, Michael J. Roberts, and Wolfram Schlenker (2012). "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Comment," *American Economic Review*, 102(7), 3749-3760.

Estimates of Control Variables with Alternative Specifications of Fixed Effects

	Parameter Estimates			Z-Scores, Difference in Means		
	Tract FE	County FE	No FE	Tract FE/ County/FE	Tract FE/ No FE	County/ No FE
Intercept	671.059600	555.333595	579.842250	78.2742	73.5446	-30.4572
Population	0.001404	0.000321	-0.000740	35.3864	73.9161	108.6385
Share 65+	0.675520	0.941643	0.973587	-39.9356	-51.8377	-9.4845
White	0.147636	0.762645	0.602638	-154.2579	-123.3069	105.9861
Hispanic/Latino	**0.042277**	**-0.474708**	**-0.199755**	97.7191	51.1696	-116.0158
Female Householder w/Kids	-27.365700	-185.683801	-277.743951	150.7583	320.3815	131.2385
SNAP	**0.571605**	**-0.292803**	**-0.749482**	157.0032	389.7010	105.2684
Owner-Occupied	0.111513	0.281964	0.174667	-38.1729	-14.8249	80.1819
Owner Occupied with Mortgage	-0.038420	0.244492	0.626782	-74.8342	-227.0314	-160.0205
No HS Diploma	**0.002170**	**-0.006454**	**-0.010148**	41.7965	114.0514	21.0050
BA or Higher	0.000086	0.000535	0.000852	-26.7337	-69.6712	-24.9992
Time Trend		0.439743	0.544822			-69.5781
Adjusted R^2	0.95	0.80	0.66			

The dependent variable is the Equifax Risk Score (a credit score)
Heteroscedasticity-Consistent Standard Errors
All variables are significant at the 99 percent confidence level
All Z-scores in columns 7-9 are significant at the 99 percent confidence level.

Difference in Parameter Values, Hurricane Variables with and without County Fixed Effects

Cat_Dist_Lag	p-value (t-dist)	Cat_Dist_Lag	p-value (t-dist)	Cat_Dist_Lag	p-value (t-dist)	Cat_Dist_Lag	p-value (t-dist)
H1_15_0	0.681	H2_15_0	0.596	H3_15_0	0.736	H4_15_0	0.774
H1_15_1	0.886	H2_15_1	0.693	H3_15_1	0.805	H4_15_1	0.843
H1_15_2	0.752	H2_15_2	0.525	H3_15_2	0.700	H4_15_2	0.908
H1_15_3	0.230	H2_15_3	0.324	H3_15_3	0.646	H4_15_3	0.973
H1_15_4	0.408	H2_15_4	0.479	H3_15_4	0.756	H4_15_4	0.959
H1_25_0	**2.7E-09**	H2_25_0	0.433	H3_25_0	0.543	H4_25_0	0.744
H1_25_1	**1.2E-07**	H2_25_1	0.587	H3_25_1	0.701	H4_25_1	0.755
H1_25_2	**4.7E-09**	H2_25_2	0.369	H3_25_2	0.486	H4_25_2	0.555
H1_25_3	**1.7E-09**	H2_25_3	0.208	H3_25_3	0.406	H4_25_3	0.684
H1_25_4	**3.6E-08**	H2_25_4	0.203	H3_25_4	0.366	H4_25_4	0.662

Values in **green** indicate a statistically significant difference in the estimated means of the variable between the models with and without county fixed effects. In the specific case here, the probably that the H1_25 variables are different is nearly 100 percent (i.e.,, in the case of H1_25_0, the probability is 1 – 2.7E-09 ≈ 1).

Results

- Model generates hundreds of parameters and associated statistics—can't discuss variable-by-variable

- Provide high-level interpretation of models with credit score on LHS
- Briefly review estimates of models with "Any Past Due" on LHS

Interpretation of Results

- Consider simplified model where credit score is given by CS, and I is the credit variable interacted with H:

$$CS = \alpha H^{2,25,2} + \delta H^{2,25,2} I$$

- Then the impact of the category 2 hurricane on CS in tract within 25 miles of hurricane, two periods ago is:

$$\frac{\partial CS}{\partial H^{2,25,2}} = \alpha^{2,25,2} + \delta^{2,25,2} I$$

- Using all LHS interaction variable at their mean values

$$\frac{\partial CS}{\partial H^{2,25,2}} = -10.11 - 1.94(\text{Card Utilization}) - 5.47(\text{LTV Proxy}) - 197.19(\text{AnyPastDue}) + 14.28(\text{Inclusion})$$

Interpretation of Results

Assume $H_{i,t}^{2,25,0} = 1 \Rightarrow$

$$H_{i,t+1}^{2,25,1} = 1$$

$$H_{i,t+2}^{2,25,2} = 1$$

$$H_{i,t+3}^{2,25,3} = 1$$

$$H_{i,t+4}^{2,25,4} = 1$$

$$\begin{aligned}
\frac{\partial CS}{\partial H^{2,25,0}} = {} & \alpha^{2,25,0} + \delta_{CdU}^{2,25,0}\left(\text{CardUtilization}\right)_t + \delta_{LTV}^{2,25,0}\text{LTV Proxy}_{\text{t}} + \delta_{PD}^{2,25,0}\left(\text{AnyPastDue}\right)_t \\
& + \delta_{PD}^{2,25,0}\left(\text{Inclusion}\right)_t + \delta_{CdU}^{2,25,1}\left(\text{CardUtilization}\right)_{t+1} + \delta_{LTV}^{2,25,1}\left(\text{LTV Proxy}\right)_{t+1} \\
& + \delta_{PD}^{2,25,1}\left(\text{AnyPastDue}\right)_{t+1} + \delta_{PD}^{2,25,1}\left(\text{Inclusion}\right)_{t+1} + \delta_{PD}^{2,25,2}\left(\text{CardUtilization}\right)_{t+2} \\
& + \delta_{LTV}^{2,25,2}\left(\text{LTV Proxy}\right)_{t+2} + \delta_{PD}^{2,25,2}\left(\text{AnyPastDue}\right)_{t+2} + \delta_{PD}^{2,25,2}\left(\text{Inclusion}\right)_{t+2} \\
& + \delta_{PD}^{2,25,3}\left(\text{CardUtilization}\right)_{t+3} + \delta_{LTV}^{2,25,3}\left(\text{LTV Proxy}\right)_{t+3} + \delta_{PD}^{2,25,3}\left(\text{AnyPastDue}\right)_{t+3} \\
& + \delta_{PD}^{2,25,3}\left(\text{Inclusion}\right)_{t+3} + \delta_{CdU}^{2,25,4}\left(\text{CardUtilization}\right)_{t+4} + \delta_{LTV}^{2,25,4}\left(\text{LTV Proxy}\right)_{t+4} \\
& + \delta_{PD}^{2,254}\left(\text{AnyPastDue}\right)_{t+4} + \delta_{PD}^{2,25,4}\left(\text{Inclusion}\right)_{t+4}
\end{aligned}$$

Interpretation of Results

- Assume average RHS credit values are fixed
- Total effect at means of RHS credit for category 1 hurricane in tract within 15 miles (column 10 in Table 3 of paper)

$$
\begin{aligned}
\frac{\partial CS}{\partial H^{2,25,0}} = {} & \alpha^{2,25,0} + \delta_{CdU}^{2,25,0}(\text{CardUtilization})_t + \delta_{LTV}^{2,25,0}\text{LTV Proxy}_{\text{t}} + \delta_{PD}^{2,25,0}(\text{AnyPastDue})_t \\
& + \delta_{PD}^{2,25,0}(\text{Inclusion})_t + \delta_{CdU}^{2,25,1}(\text{CardUtilization})_{t+1} + \delta_{LTV}^{2,25,1}(\text{LTV Proxy})_{t+1} \\
& + \delta_{PD}^{2,25,1}(\text{AnyPastDue})_{t+1} + \delta_{PD}^{2,25,1}(\text{Inclusion})_{t+1} + \delta_{PD}^{2,25,2}(\text{CardUtilization})_{t+2} \\
& + \delta_{LTV}^{2,25,2}(\text{LTV Proxy})_{t+2} + \delta_{PD}^{2,25,2}(\text{AnyPastDue})_{t+2} + \delta_{PD}^{2,25,2}(\text{Inclusion})_{t+2} \\
& + \delta_{PD}^{2,25,3}(\text{CardUtilization})_{t+3} + \delta_{LTV}^{2,25,3}(\text{LTV Proxy})_{t+3} + \delta_{PD}^{2,25,3}(\text{AnyPastDue})_{t+3} \\
& + \delta_{PD}^{2,25,3}(\text{Inclusion})_{t+3} + \delta_{CdU}^{2,25,4}(\text{CardUtilization})_{t+4} + \delta_{LTV}^{2,25,4}(\text{LTV Proxy})_{t+4} \\
& + \delta_{PD}^{2,254}(\text{AnyPastDue})_{t+4} + \delta_{PD}^{2,25,4}(\text{Inclusion})_{t+4}
\end{aligned}
$$

$$
\frac{\partial CS}{\partial H^{1,15,0}} = \sum_{l=0}^{4} \alpha^{1,15l} + \sum_{r=1}^{4} \sum_{l=0}^{4} \delta^{1,15,l}\, \bar{I}^{\,r} = -3.1050 - 5.8914 - 3.2879 - 4.3744 - 4.9410 \approx -21.6
$$

Results

- Results are mixed, but typically show negative impacts on personal finances across hurricanes of varying intensity
- Generally, hurricanes lead to lower values of credit score in tracts within 15-mile band of hurricane
- Generally, hurricanes lead to higher values of credit score in tracts within 25-mile band of hurricane
- Tracts with a typical consumer who has better credit standing, all else equal, is less likely to see a hurricane lead to more past due bills (share in tract with)

Additional Models

- Risk Score
  - Risk Score (lag 2)
  - Any Past Due (lag 2)
  - Bank Card Utilization Rate (lag 2)
- Any Past Due
  - Risk Score (lag 2)
  - Any Past Due (lag 2)
  - Bank Card Utilization Rate (lag 2)
- Bank Card Utilization
  - Risk Score (lag 2)
  - Any Past Due (lag 2)
  - Bank Card Utilization Rate (lag 2)
- Inclusion?

FEDERAL RESERVE BANK *of* KANSAS CITY

Contact Information:

Kelly D. Edmiston | Senior Economist
Community Development Department
Federal Reserve Bank Of Kansas City
1 Memorial Drive | Kansas City, MO 64198
kelly.edmiston@kc.frb.org

EVALUATING THE ACCURACY OF ECONOMIC IMPACT ESTIMATES OF A 2013 BEEF PLANT CLOSURE

Rebekka Dudensing[1], Bridget Guerrero[2], and Steve Amosson[1]
[1]Texas A&M AgriLife Extension Service, [2]West Texas A&M University

2017 Mid-Continent Regional Science Association Conference
Toledo, Ohio, June 7-9, 2017

Cargill Plant Closure

In January 2013, the Plainview, Texas Cargill meat-packing plant announced its closure, resulting in losses of

- 2012 sales of $1.67 Billion per ReferenceUSA
- 2,000+ direct jobs
- equivalent to 13% of the labor force in Hale County, where most employees lived

Methods

- Goals:
  - Build policy-relevant understanding and reduce fear
  - Accurate but conservative
- Account for labor from surrounding counties
  - Estimate employees by county of residence
  - Remove induced effects from nonlocal labor
- Prevent double counting of beef production losses
  - Cattle numbers were already down, wrong to double count
  - Zeroed local beef purchases

Estimated direct employment and labor income losses by county

County	Employment	Labor Income
Castro	8	$224,448
Floyd	58	$1,627,248
Hale	**1,462**	**$41,017,872**
Lamb	40	$1,122,240
Swisher	50	$1,402,800
Other Counties	538	$15,094,128
Total	**2,156**	**$60,488,736**

Estimated Impacts

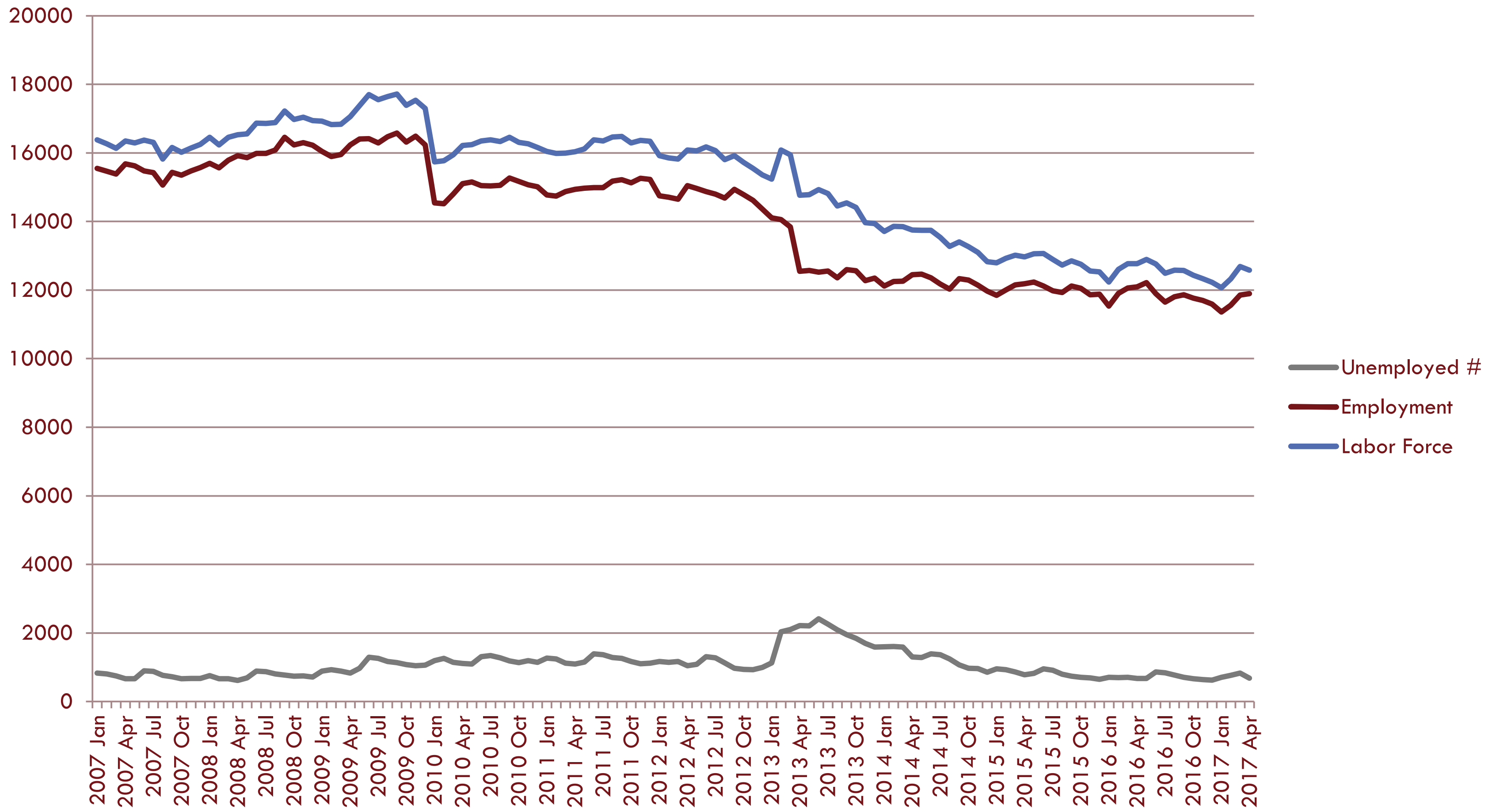
Impact Type	Output	Value Added	Labor Income	Employment
Direct Effect	$866.6 M	$199.0 M	$45.7 M	1,462.00
Indirect Effect	$132.9 M	$63.9 M	$39.8 M	767.4
Induced Effect	$36.9 M	$22.1 M	$11.7 M	366
Total Effect	$1.0 B	$285.9 M	$97.2 M	2,595.40

Ability to Validate Results

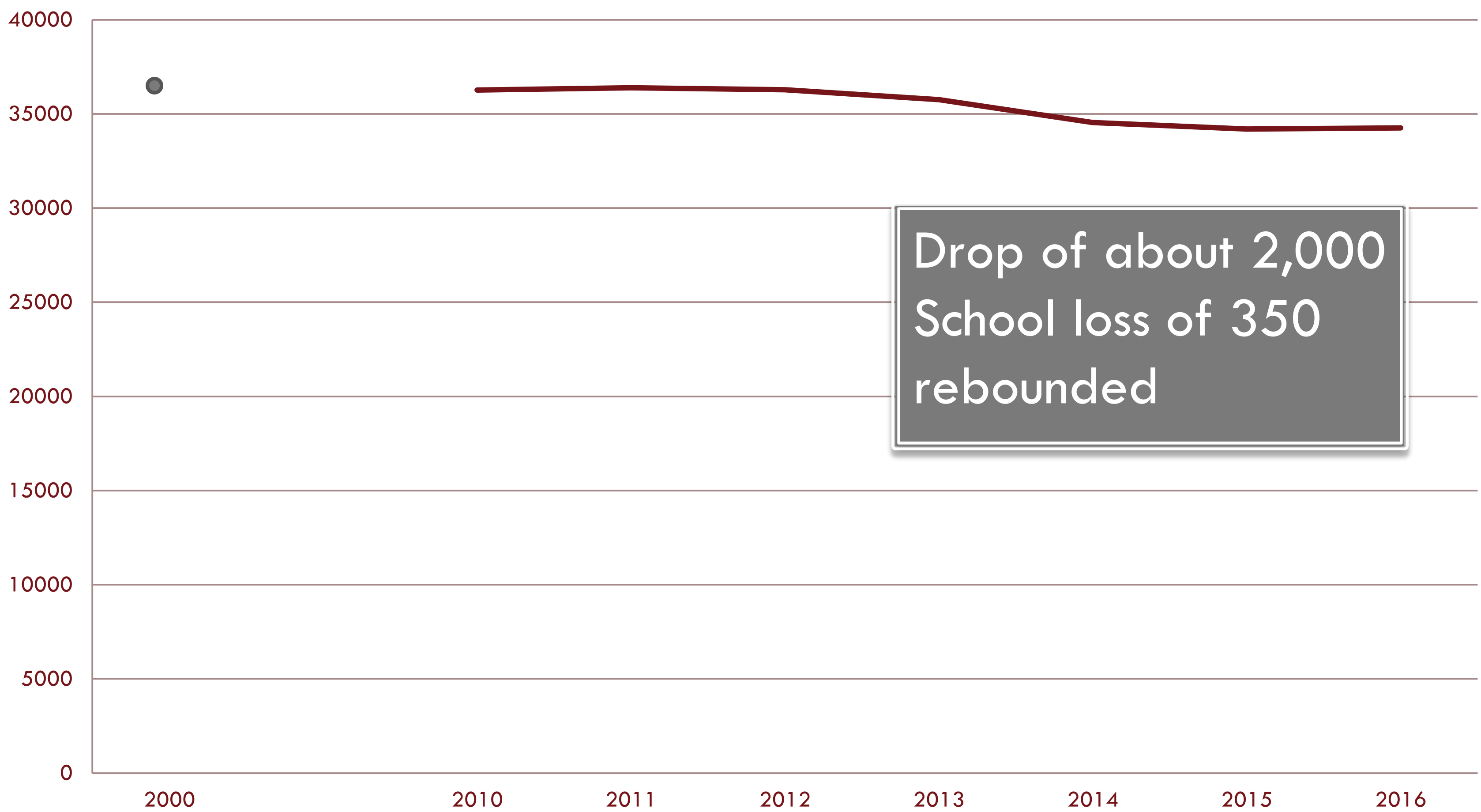
- Large loss in a small economy
- Concentrated in a single, identifiable industry
- Sustained/permanent loss
- Ongoing interaction with local and regional economic and political leaders to account for both resultant and exogenous activity

SET
Stronger Economies Together

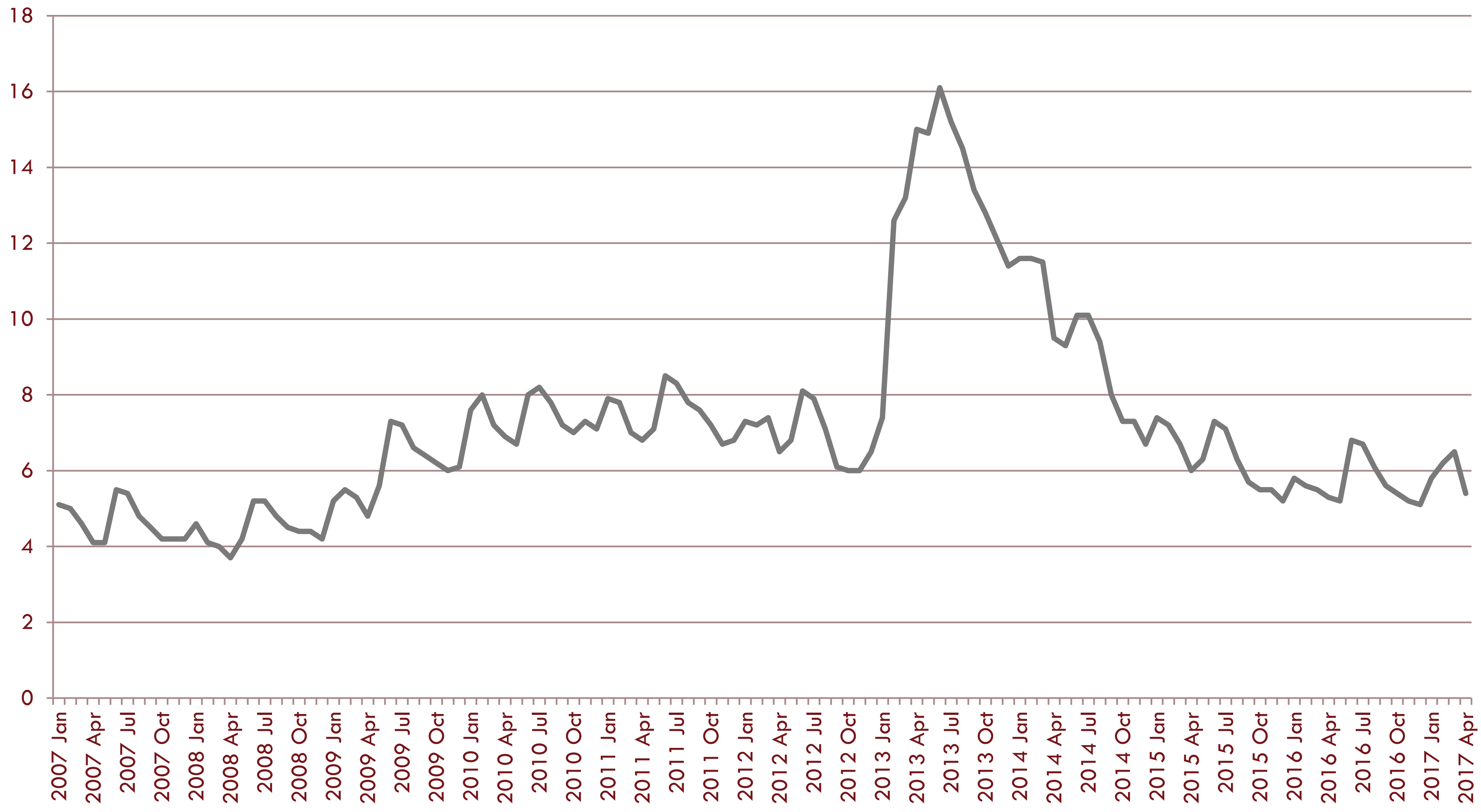
Hale County Labor (BLS)



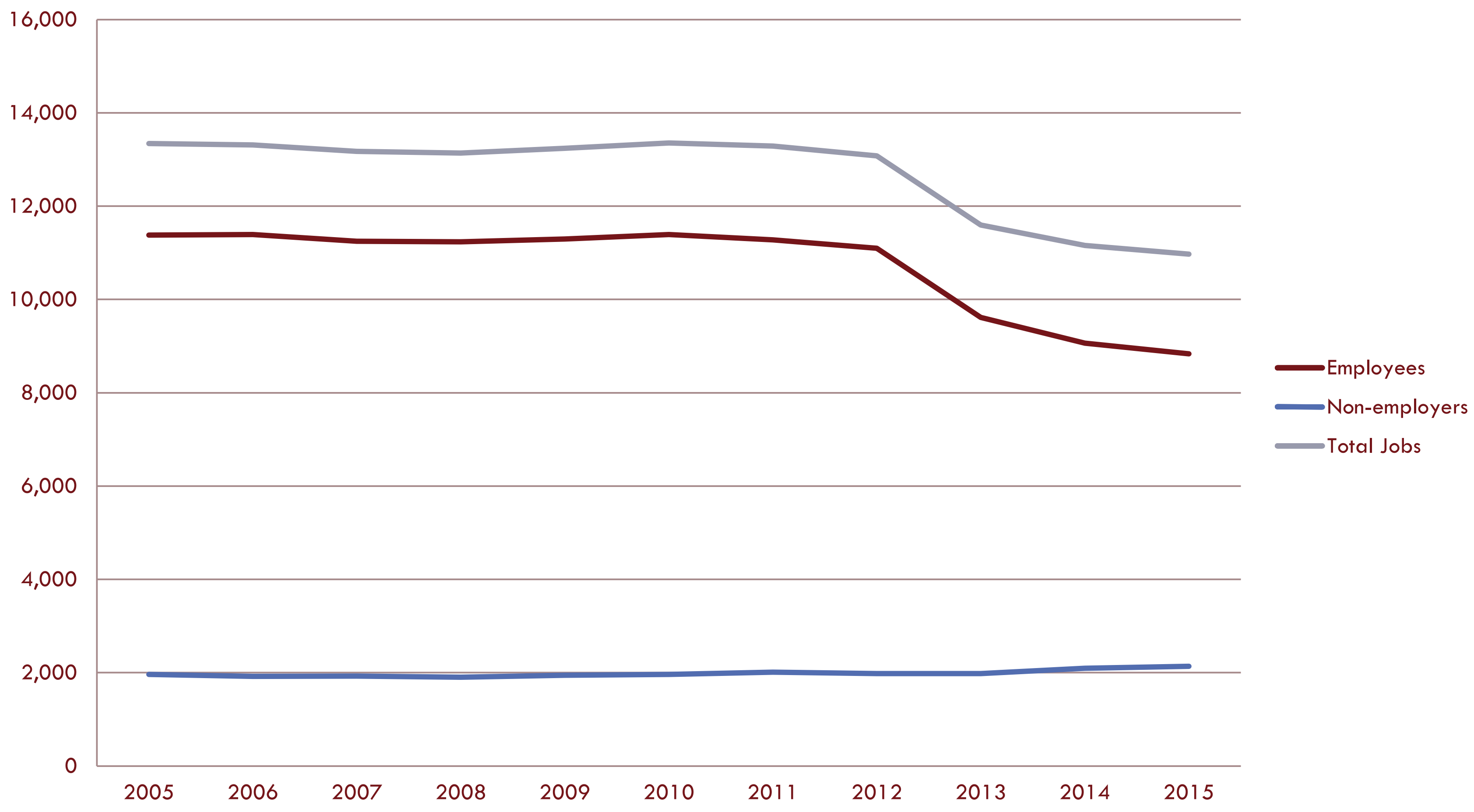
Population (Census)



Hale County Unemployment Rate



Employment and Non-employers (CBP)



Comparing estimated and actual employment

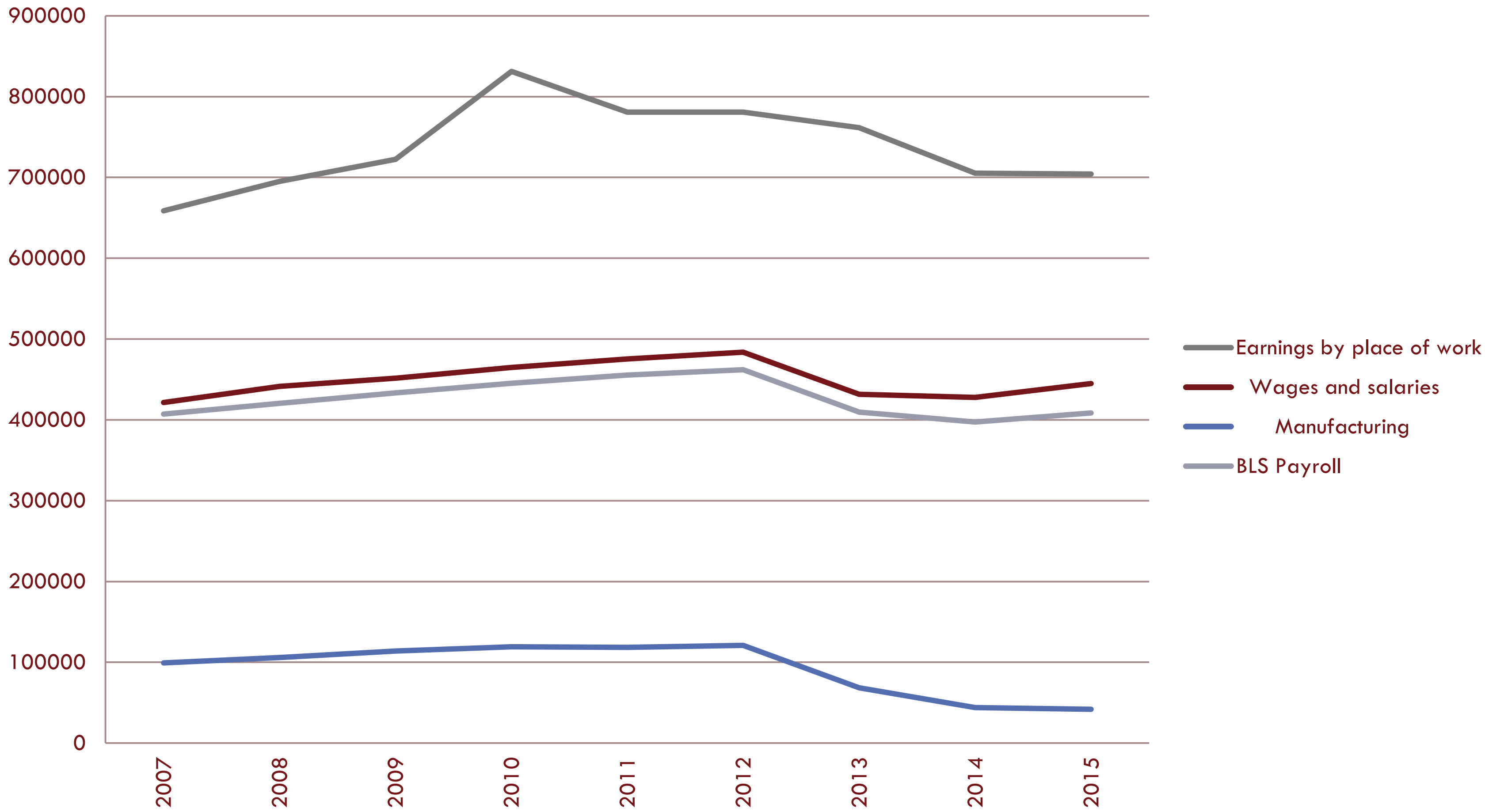
- Estimated losses of 2,595 to Hale County
- BLS Actual = 2,225 Jan 2013 – Dec 2015
- BLS Actual = 2,250 Jan 2013 – Mar 2017
- BEA Actual = 2,303 2012 – 2014
- BEA Actual = 2,185 2012 – 2015
- CBP w NE Actual = 2,109 2012 – 2015

Comparing estimated and actual employment

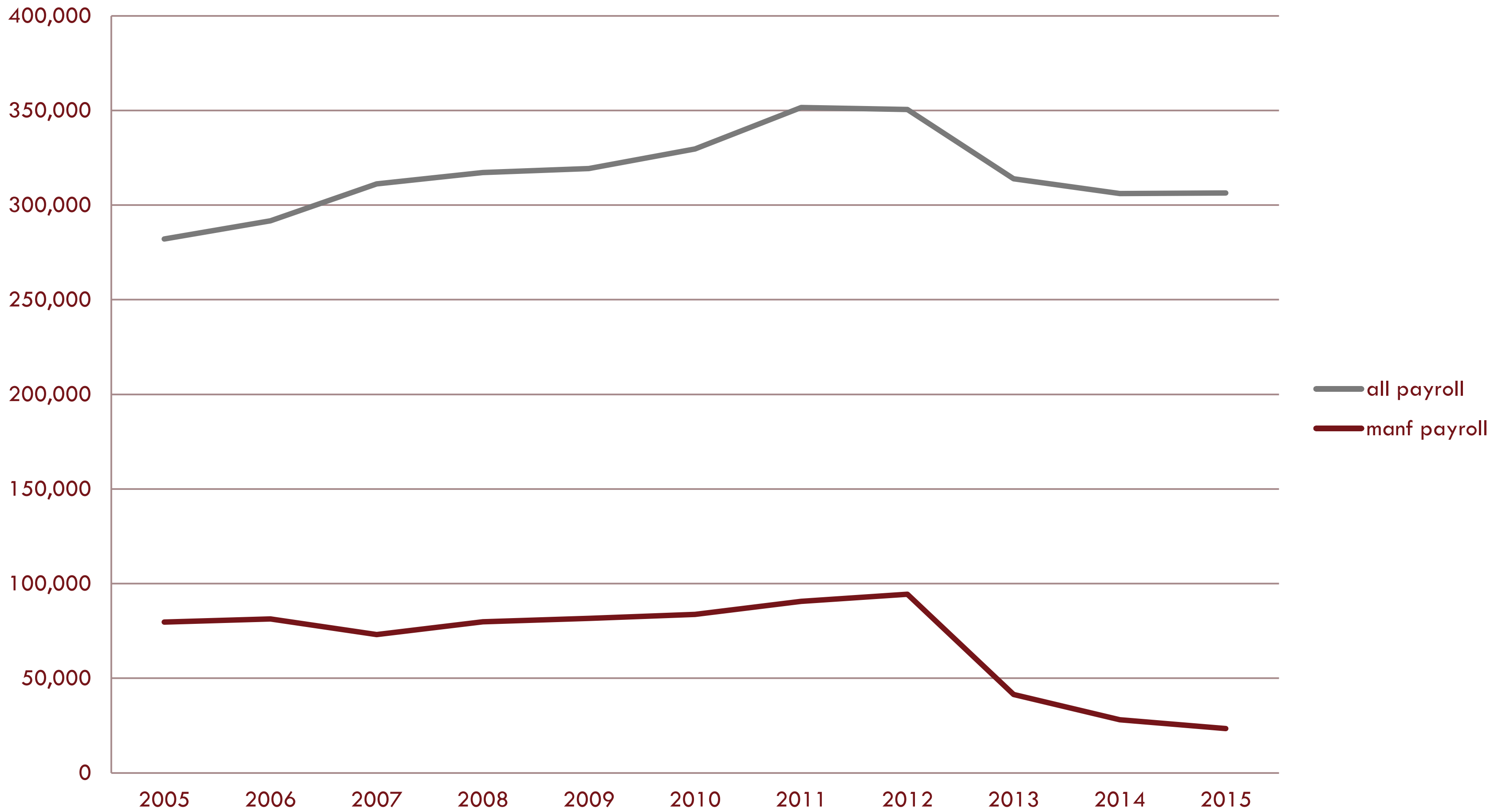
- BEA Manufacturing loss = 2,043 2012-2014
- BLS Manufacturing loss = 1,874 2012-2014
- CBP Manufacturing Loss = 1,926 2012-2015

- Overestimated. But partially offset by new car dealership cluster, wind distribution, and hospital expansion. So probably not too bad.

Personal Income (BEA)



Payroll (CBP)



400,000
350,000
300,000
250,000
200,000
150,000
100,000
50,000
0
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
all payroll
manf payroll

Labor Income / Earnings

- Estimated losses of $97.1 million to Hale County
- BEA earnings loss = $56.0 million 2012 – 2014
- CBP payroll loss = 44.4 million 2012 – 2014

- Estimated losses of $45.7 million to Hale County
- BEA manf earnings loss = $77.1 million 2012 –14
- CBP payroll loss = 44.4 million 2012 - 2014

Labor Income / Earnings

- Underestimated direct labor income loss
- Overestimated total labor income loss
- Labor income loss was mitigated by other industries, especially in the 2nd year (2013-14)
- Transfer payments up
- Indirect effects virtually non-existent

Bright Spots

- 3 new car dealerships
- Wind energy distribution
  - Transportation
  - Retail
  - Hotel
- Hospital expansion
- Temporary adjustments in oil fields

Estimated Impacts

Impact Type	Output	Value Added	Labor Income	Employment
Direct Effect	$866.6 M	$199.0 M	$45.7 M	1,462.00
~~Indirect Effect~~	~~$132.9 M~~	~~$63.9 M~~	~~$39.8 M~~	~~767.4~~
Induced Effect	$36.9 M	$22.1 M	$11.7 M	366
~~Total Effect~~	~~$1.0 B~~	~~$285.9 M~~	~~$97.2 M~~	~~2,595.40~~
Direct + Induced	$903.5 M	$221.9 M	$57.4 M	1,828.0

IMPLAN Variation Year-to-Year

Year	Industry Code	Output	Employee Compensation
2009	59	$947,225,024	$76,026,480
2012	59	$629,761,719	$70,062,576
2013	89	$481,030,945	$30,793,751
2014	89	$160,829,117	$9,273,456

IMPLAN Meat Processing Sector Multipliers

	Output	Value Added	Labor Income	Employ-ment
2009	1.2639	0.3660	0.1378	4.0259
2012	1.1514	0.1604	0.1534	4.2362
2013	1.1788	0.2383	0.1350	3.0200

Impacts using different data years

	Output	Value Added	Labor Income	Employ-ment
2009	$1.0 B	$285.9 M	$97.2 M	2,595.4
2012	$662.1 M	$69.1 M	$73.8 M	1,759.0
2013	$1.4 B	$254.5 M	$139.7 M	2,728.9

	Estimated Direct
2009	$866.6 M
2012	$626.1 M
2013	$1.2 B

Conclusions—Impact Analysis

- I-O performed well for this plant closure with ongoing losses (at least two years out)
- The data year matters and should be selected to match the event or approximate current conditions
- Test data and assumptions against other IMPLAN and non-IMPLAN data and studies
- Customization of the model to local conditions is important if possible

Conclusions—Community Response

- **Economies are resilient**
- Job re-training is important
- Self-employment may become more important and can be cultivated
- Look for new competitive advantages

Thank you.

Rebekka Dudensing, PhD
rmdudensing@tamu.edu
(979) 845-1719
@rmdudensing
@AgEcoExt

Socio-demographic Predictors of Personal and Perceived Stigma in the United States

Paula K. Miller, Ohio University
Courtney Cuthbertson, Michigan State University
Scott Loveridge, Michigan State University
Rob Schupp, Michigan State University

Background on Behavioral Health

- Behavioral health is a broad category, which encompasses mental illnesses such as depression, and substance abuse.
- In the US, approximately 1 in 5 adults aged 18 or over experienced behavioral health issues in the past year (Center for Behavioral Health Statistics and Quality 2015).
- One in three individuals never receive or complete treatment for behavioral health issues, partly due to fear of discrimination and negative beliefs about mental illness (Corrigan 2004).

Economic Impact on Community

- Taken together, behavioral health issues have severe economic impacts on our communities, and our nation as a whole, including:
  - $193.2 billion in lost earnings per year (Kessler et. al, 2008)
  - $247 billion cost for youth behavioral health issues, including treatment costs and lost productivity (Eisenberg and Neighbors, 2007).

Stigma

- Stigma is a negative belief or label that is attached to a particular person or behavior.
  - Examples?
- Stigma is often measured in sociological research through the use of social distance scales (Link et al. 1987).
- More recent research conducted primarily in Japan and Australia distinguish between personal and perceived stigma. (Griffiths et al. 2006, Griffiths, Christensen and Jorm 2008)
  - Personal stigma
  - Perceived community stigma

Socio-Demographics and Stigma

- Few studies examine whether respondents from different racial backgrounds report similar levels of stigma. Existing studies show minimal impact.
- Differences in stigma by gender, age, education, income, and urban/rural residency are understudied.

Stigma Towards Different Behavioral Health Issues

- Most research explores stigma towards depression.
- Stigma related to drug and alcohol abuse is often higher than stigma related to other kinds of behavioral health issues (Martin, Pescosolido and Tuch 2000).
- Few studies have examined stigma towards anxiety.

Research Questions

- How socio-demographic factors impact **personal** stigma towards:
  - Depression
  - Anxiety
  - Alcohol abuse, and
  - Prescription drug misuse
- How socio-demographic factors impact **perceived** community level stigma towards:
  - Depression
  - Anxiety
  - Alcohol abuse, and
  - Prescription drug misuse

Data and Methods

- Data
  - Community Assessment and Education to Promote Behavioral Health Planning and Evaluation (CAPE) Behavioral Health Survey
    - Nationally representative
    - Data collected online using Survey Sample International
    - Respondents were asked a series of questions about personal and perceived community stigma after reading a vignette (Jorm et. al, 1997) about an individual experiencing symptoms of depression, anxiety, alcohol abuse, or prescription drug misuse.
    - Total N=4398
- Methods
  - Initial analysis using multivariate linear regression

Independent Variables

- Age
  - 45 years (mean)
- Education
  - Associate's degree (mean)
- Race
  - White, 82.9%
  - Black, 7.5%
  - Hispanic, 4.5%
- Gender
  - Female, 57.1%
- Urbanicity
  - Urban, 37.2%
  - Suburban, 35.7%
  - Rural, 27.1%
- Income
  - $50,000 (mean)

+ Dependent Variables

- **Personal** Stigma: Participant's self-report of their own negative and unfair beliefs towards individuals experiencing behavioral health issues.
  - Rated on Likert scale of 1=strongly disagree to 5=strongly agree
    - Examples: People with a problem like X's are dangerous; If I had a problem like X's I would not tell anyone

- **Perceived** Community Level Stigma: Participant's report of the negative and unfair beliefs towards individuals experiencing behavioral health issues that exist in their community.
  - Rated on Likert scale of 1=strongly disagree to 5=strongly agree
    - Examples: Most people in my community believe that people with a problem like X's are dangerous; If they had a problem like X's people in my community would not tell anyone

Table 1: Personal Stigma, by Behavioral Health Category				
	Depression	Anxiety	Alcohol Abuse	PDM
Age	-.197***	-.242***	-.137***	-.203**
Education	.133***	.150*	.079	.036
Black (0=white)	-.050	-.279	-.010	-.200
Hispanic	.181	-.708	-.207	.219
Asian	-.944***	-.289	-.592	.141
Other Race	-.250	-.955	-.669	-.161
Female	-.978***	-1.07***	-.575**	-.801***
Suburban (0=urban)	-1.07***	-1.28***	-.647**	-978***
Rural	-1.17***	-1.15***	-.816**	-.793**
Income	.058**	.102*	.109*	.116*
Constant	3.55***	3.77***	3.26***	4.03***
Adj. R2	20.2%	23.6%	9.8%	15.1%

Table 2: Perceived Community Stigma, by Behavioral Health Category

	Depression	Anxiety	Alcohol Abuse	PDM
Age	-.172***	-.184***	-.115**	-.222***
Education	.177***	.120	.132	.177*
Black (0=white)	-.254	-.295	-.104	-.992
Hispanic	-.383	-1.02	-.908	-.218
Asian	-.910**	-.984	-1.08	-1.05
Other Race	-.309	-.640	-.078	-1.36
Female	-.302*	-.552*	-.195	.166
Suburban (0=urban)	-.562***	-1.12***	.059	-.348
Rural	-.612***	-.399	.129	-.026
Income	-.005	.150*	.139*	.042
Constant	4.48***	4.22***	3.57***	5.00***
Adj. R2	5.9%	9.1%	3.0%	6.5%

Main Takeaways

- Respondents who are younger, more highly educated, male, urban, and have higher household incomes are more likely to demonstrate both personal and perceived community stigma.
- The impact of socio-demographic factors on stigma varies by the particular behavioral health issue being addressed.
- Socio-demographic factors are stronger predictors of personal stigma than perceived community stigma.

Significance

- Stigma is a key component of mental health literacy.
- Increased mental health literacy leads to greater community cohesion.
- Understanding socio-demographic predictors of stigma provides researchers, policy makers, and practitioners with useful information to target mental health literacy efforts towards groups with higher levels of stigma.

Limitations and Future Research

- Ordered logistic regression
- Replication of this study, especially in the United States
- Exploration of additional predictors of stigma, including structural and communal conditions

Thank You and Questions

- Contact: mille995@msu.edu with any questions

- Community Assessment and Education to Promote Behavioral Health Planning and Evaluation (CAPE) is dedicated to identifying and sharing best practices for benchmarking community behavioral health. More information on the CAPE project can be accessed at www.healthbench.info. We can also be found on Twitter (@HealthBench) and Facebook (facebook.com/healthbench.info). CAPE is supported by the National Institute of Food and Agriculture (NIFA), under Agreement No. 2013-48765-21544, using funding from HHS SAMHSA.

References

Center for Behavioral Health Statistics and Quality. 2015. "Behavioral Health Trends in the United States: Results from the 2014 National Survey on Drug Use and Health.", Vol. HHS Publication No. SMA 15-4927, NSDUH Series H-50.

Corrigan, P. 2004. "How Stigma Interferes with Mental Health Care." *American Psychologist* 59(7):614.

Eisenberg, D., & Neighbors, K. 2007. Economics of Preventing Mental Disorders and Substance Abuse Among Young People. Paper commissioned by the Committee on Prevention of Mental Disorders and Substance Abuse Among Children, Youth, and Young Adults. Washington, DC.

Griffiths, K., Y. Nakane, H. Christensen, K. Yoshioka, A. Jorm and H. Nakane. 2006. "Stigma in Response to Mental Disorders: A Comparison of Australia and Japan." *BMC psychiatry* 6(1):1.

Griffiths, K., H. Christensen and A. Jorm. 2008. "Predictors of Depression Stigma." *BMC psychiatry* 8(1):1.

Jorm, A., A. Korten, P. Jacomb, H. Christensen, B. Rodgers and P. Pollitt. 1997. "Mental Health Literacy: A Survey of the Public's Ability to Recognise Mental Disorders and Their Beliefs About the Effectiveness of Treatment." *Medical journal of Australia* 166(4):182-86.

Kessler, R., Heeringa, S., Lakoma, M., Petukhova, M., Rupp, A., Schoenbaum, M., et al. (2008). The individual-level and societal-level effects of mental disorders on earnings in the United States: Results from the National Comorbidity Survey Replication. American Journal of Psychiatry, 165(6), 703-11.

Link, B., F. Cullen, J. Frank and J. Wozniak. 1987. "The Social Rejection of Former Mental Patients: Understanding Why Labels Matter." *American Journal of Sociology*:1461-500.

Martin, J., B. Pescosolido and S. Tuch. 2000. "Of Fear and Loathing: The Role of Disturbing Behavior,'Labels, and Causal Attributions in Shaping Public Attitudes toward People with Mental Illness." *Journal of health and social behavior*:208-23.