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

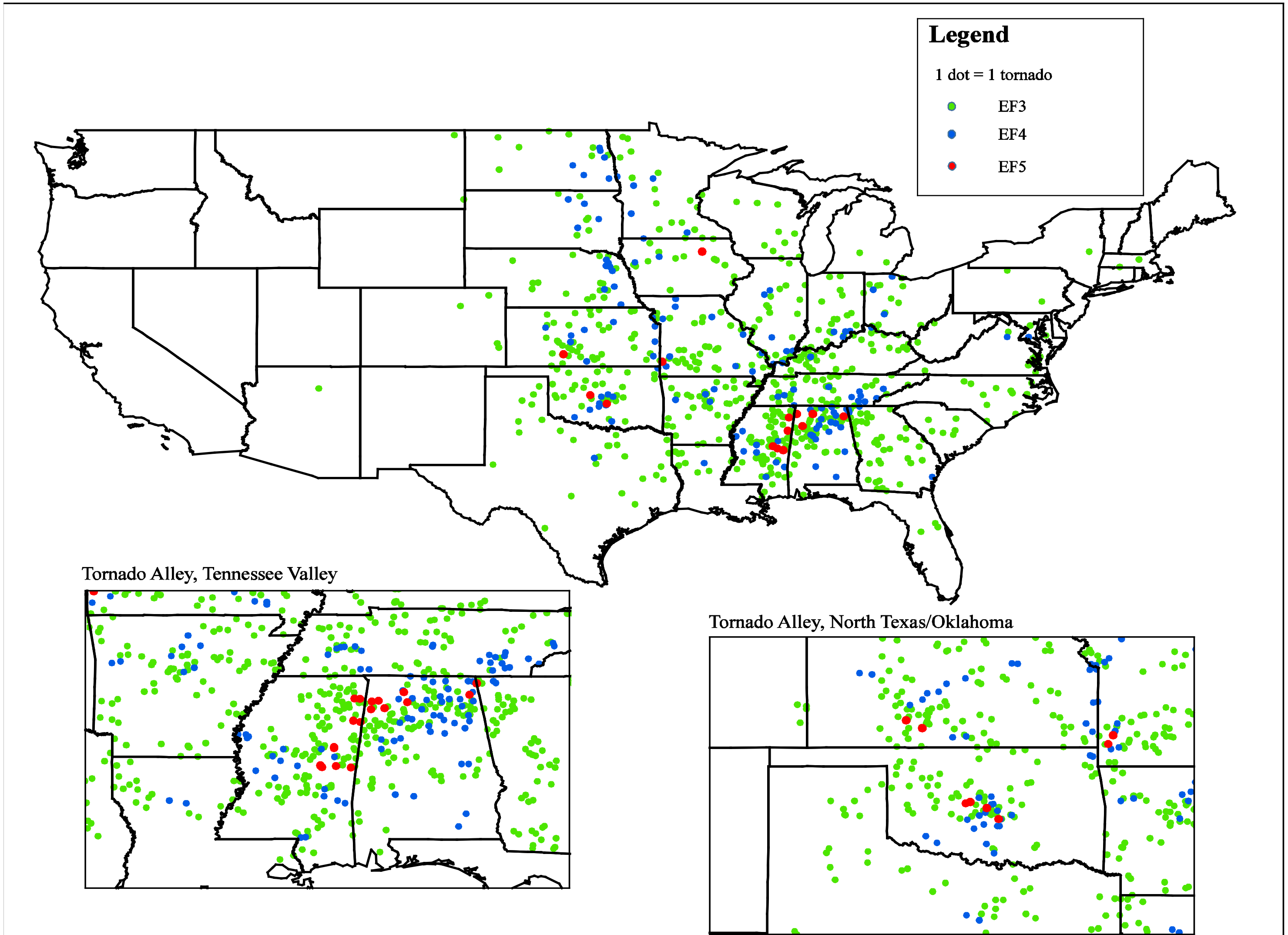
Foundations: "Hazards are natural . . . but disasters are not" (Cannon, 2004)

- **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?

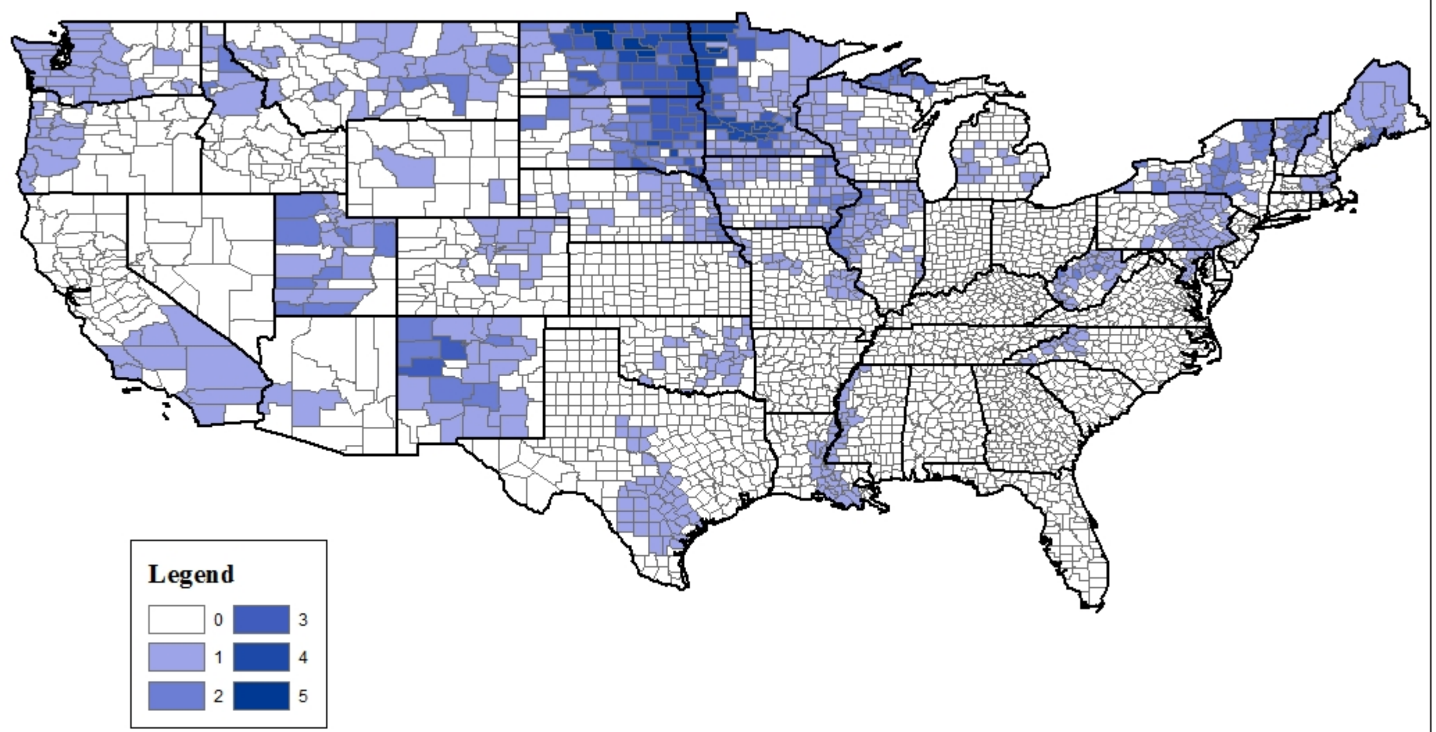
- Good data are available from quality source
- Can be tracked through census tracts at specific times and with good precision
  - Tornados can be identified geographically, but not the path, or with any precision, intensity
  - Earthquakes, floods, and wildfire require using disaster declarations at 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

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

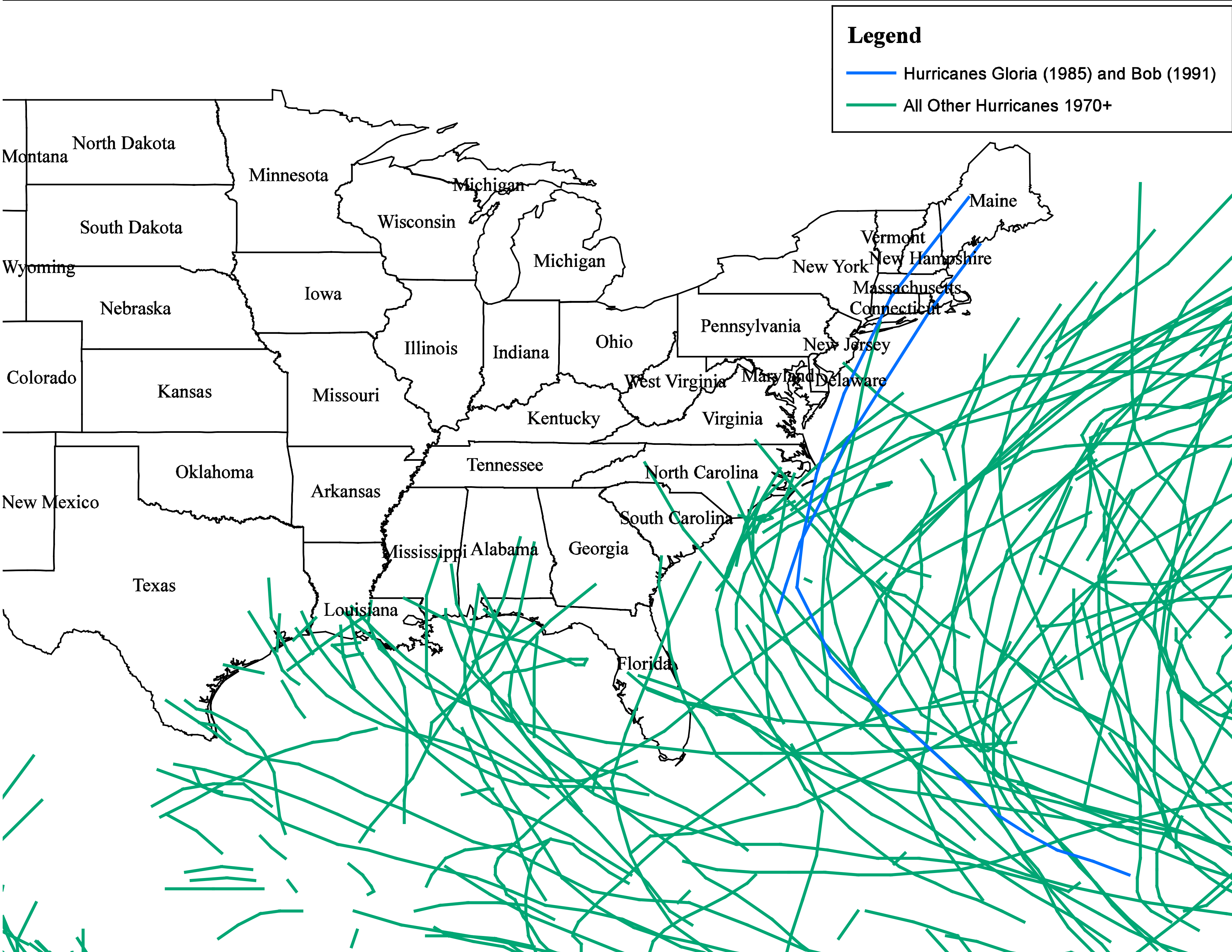
$$\log RR \sim N$$

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

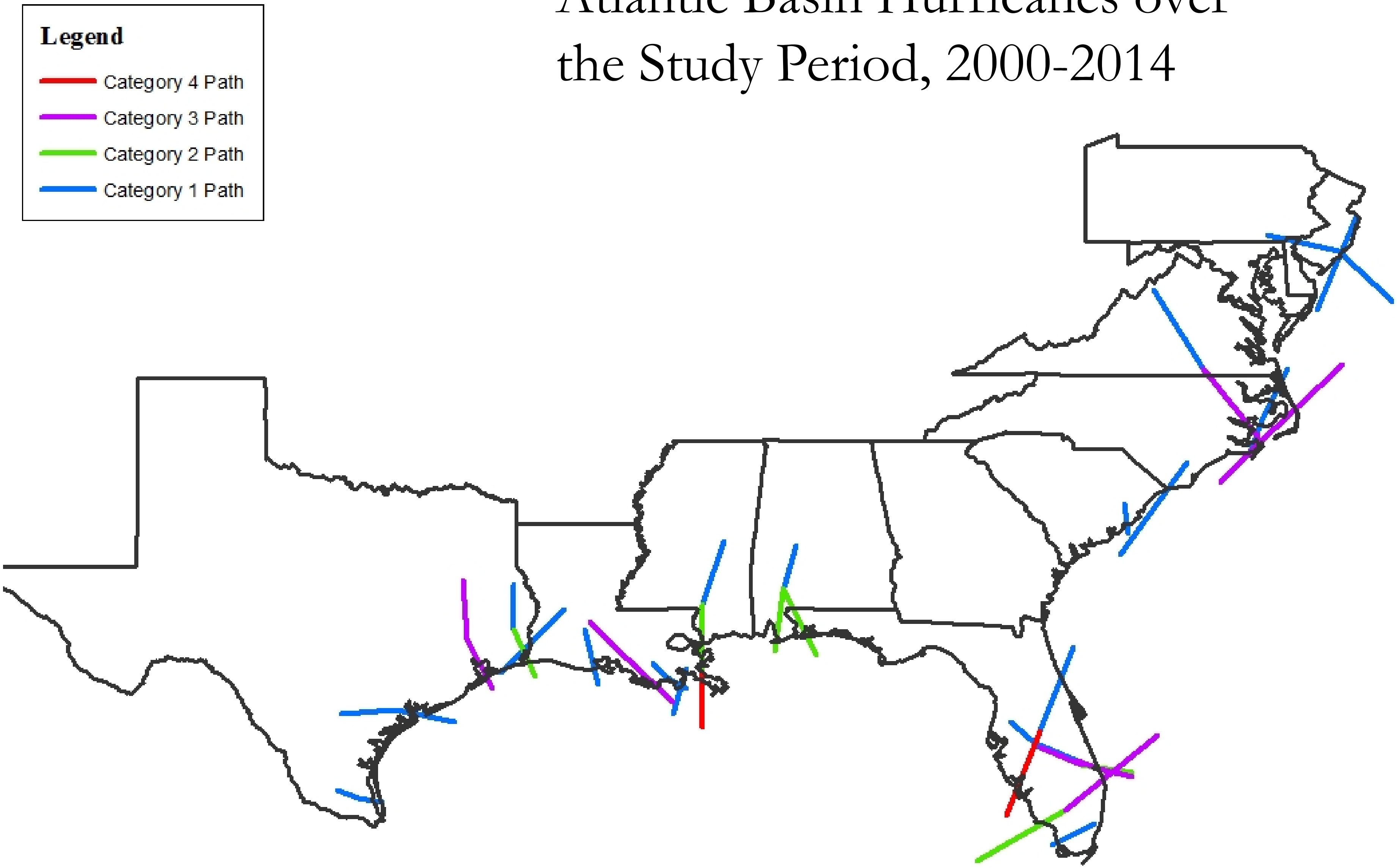
$$Z = \frac{\log RR}{\sigma} = \frac{0.1316}{0.0310} = 4.25$$

Exogeneity

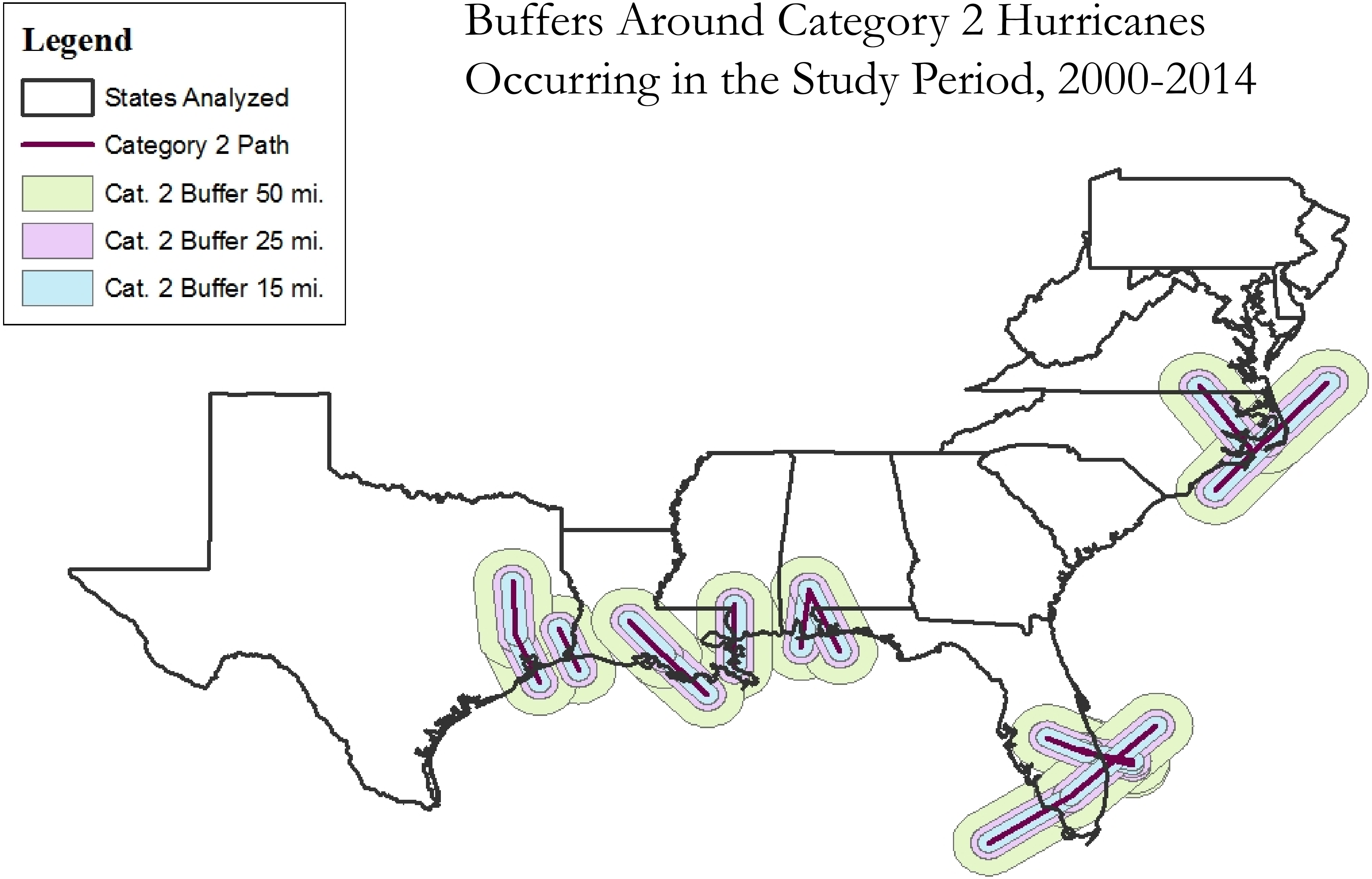
- Still, perceptions of risks by most are overly optimistic
  - Rethans (1979): an "overwhelming majority" of respondents to a random, stratified national survey reported that their fatality risk associated with traffic accidents was below normal
  - Viscusi and Zeckhauser (2006) evaluated perceptions 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
South Dakota
Wyoming
Nebraska
Iowa
Wisconsin
Michigan
Michigan
Colorado
Kansas
Missouri
Illinois
Indiana
Ohio
Pennsylvania
New York
Vermont
New Hampshire
Maine
Massachusetts
Connecticut
New Jersey
Maryland
Delaware
West Virginia
Virginia
Kentucky
Tennessee
North Carolina
South Carolina
Georgia
Alabama
Mississippi
Arkansas
Oklahoma
New Mexico
Texas
Louisiana
Florida

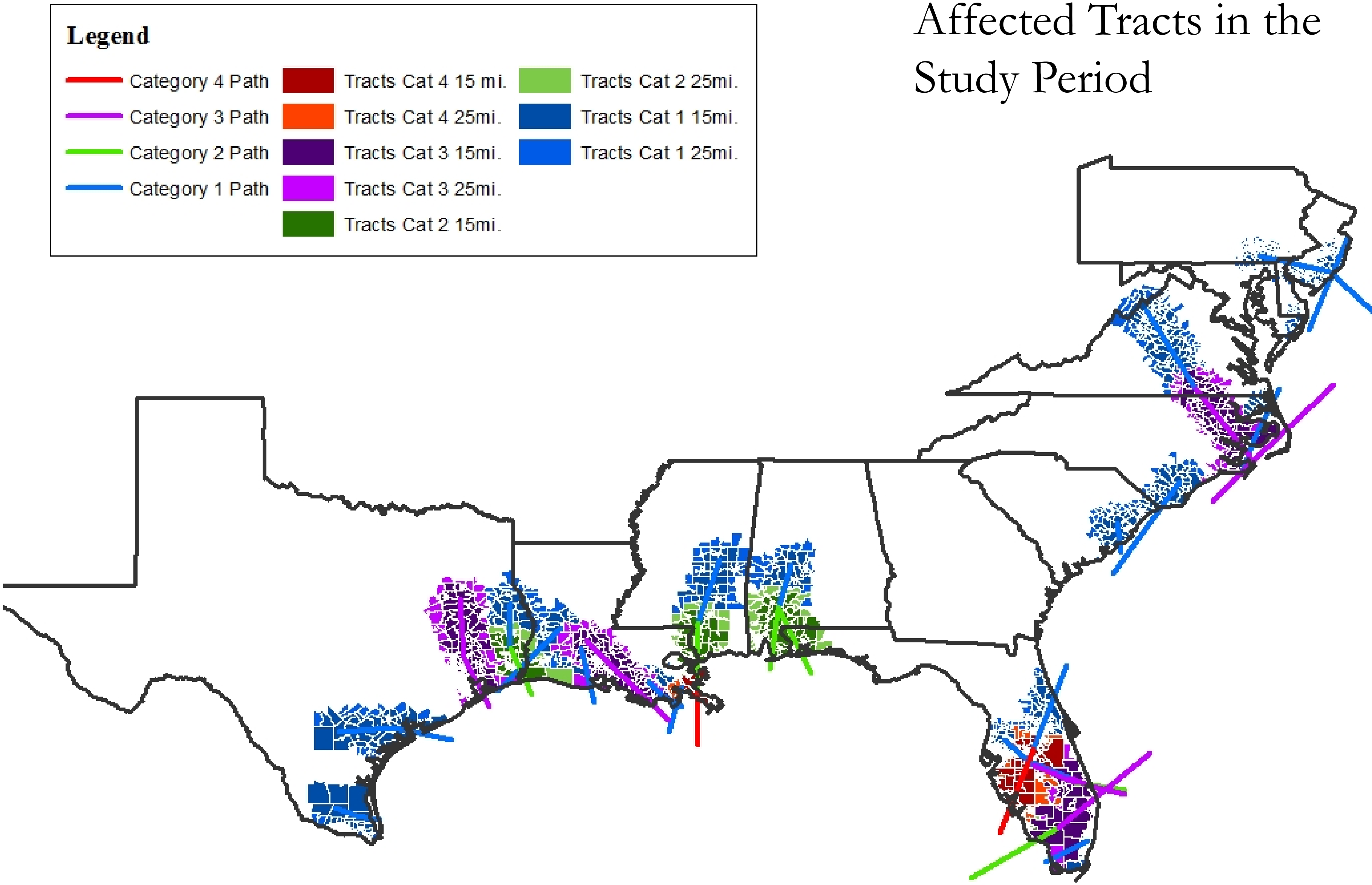
Atlantic Basin Hurricanes over the Study Period, 2000-2014



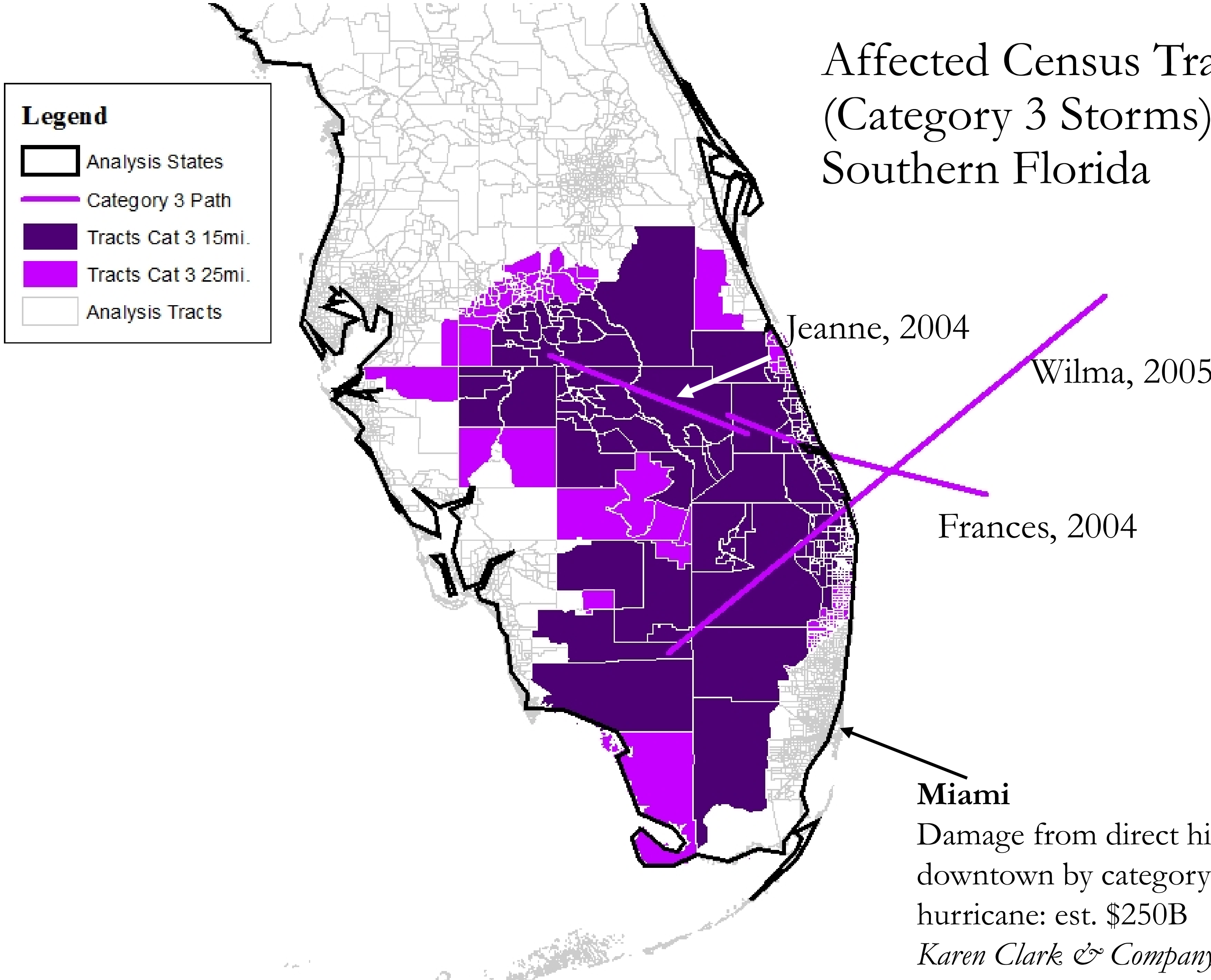
Buffers Around Category 2 Hurricanes Occurring in the Study Period, 2000-2014



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)

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

- **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 $\mathbf{H}_{it}' \in \mathbf{H}$

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

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