A Theory of and Research Note on Natural Hazards, Disaster Risk, and Urban Sprawl

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Abstract

This research note puts forth the theory that there is a small but important connection between urban sprawl and natural hazards in that the size and layout of sprawled regions make them more likely to suffer a natural hazards incident. Sprawled metro areas are hypothesized to take up more space than more compact ones, which means that due to sheer land area size, a tornado, hurricane, flash flood, etc., has a greater likelihood of occurring in more frequent numbers in sprawled metro areas than would be the case in smaller, less sprawled regions, all else held constant. Some exploratory and preliminary empirical analysis is offered to support the theory of some type urban sprawl and natural hazards correlation.

Key words: disasters, natural hazards, post disaster, urban economics, urban planning, urban sprawl

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Introduction

The average size in square miles for US metro areas in 2010 was slightly over 300 square miles with many areas constituting at least 1,000 square miles or more (US Bureau of the Census 2010). Over the last several decades, average US metro area size, the number of metro areas, and the number of counties that constitute them have increased as US population and housing number units have increased (US Bureau of the Census 2010). A possible factor causing US metro area size to vary from one region to another after controlling for population could be the degree of low density residential and commercial development and greater reliance on motor vehicle transportation so that some metro regions are more densely populated and "less sprawled" than others (Ewing and Hamidi 2014).

The fact that some areas are more "spread out" or sprawled geographically than others of roughly the same population size would seem to boost the probability that a flood, tornado, hurricane, or earthquake could impact the region at any given time, all else held constant including the region's climate. For example, for two urban areas of equal population with one occupying a greater number of square miles than another, the probability of the larger one being touched by tornadoes on a more frequent basis than the smaller one is greater. That is, if tornado occurrence is likely in a particular US region during certain times of the year, yet the number and severity or sizes of tornadoes are variable each season, then a metro region with an expanse of 1,500 square miles has a higher probably of tornado incident when compared to one with a 1,000 square mile area, all else held constant.

For the US, the state of Florida and the "Tornado Alley" and "Dixie Alley" regions are at high risk of tornado incidence during different times of the year. Tornado Alley is comprised mostly of Midwestern, Great Plains and some Southern US states whereas Dixie Alley states are mostly along the Gulf Coast (US NOAA Centers for Environmental Information n.d.). These states typically have the highest incidents of tornadoes per 10,000 square miles each year (US NOAA Centers for Environmental Information n.d.). These regions are also typically considered as those that have the greatest number of sprawled metro areas (Ewing and Hamidi 2014).

Hurricanes have a circular shape at their mature stage and can have a wind force that can span several hundred miles in diameter with the greatest wind speeds (> 73 mph) usually spanning across a 100 mile diameter, although wind speed impacts diminish as a hurricane hits land and the coastline (hurricanescience.org). It is more difficult to say whether less sprawled and less spread out regions are less immune to hurricane damage because the sheer size of hurricane fronts would seem to leave few areas of any sized region untouched. Belasen and Polachek (2008) find that no part of Florida is immune from hurricane disaster effects, although coastal counties are impacted to a much greater extent with regard to re-building costs. Zaninetti (2007) argues that much of the casualties and damages suffered by New Orleans during and after Hurricane Katrina could be attributed to the sprawled development of New Orleans in that white flight to New Orleans area suburbs after World War II weakened the city's tax base, which in turn made it more difficult for the city to prevent and mitigate future hurricane incidents. If better urban planning and less sprawl (or greater compactness) occur together, then one can argue that less sprawled regions would be less likely to leave certain areas vulnerable to hurricanes by limiting coastline development and by providing for certain safeguards and mitigation practices to prevent hurricane damage.

Likewise, planning to minimize potential earthquake damage can be linked to better urban planning with regard to natural hazards mitigation (Benson and Clay 2004, Chhibber and Laajaj 2013). Development away from fault lines may mitigate sprawled development depending upon where new development is permitted. US earthquakes associated with the greatest amount of damage and number of casualties have typically occurred in California over the last century (US Geological Survey 2015). Finally, flood losses can be minimized by hazards mitigation tools such as flood walls, large drainage basins, and adequate storm sewers (Benson and Clay 2004, Chhibber and Laajaj 2013). More compact areas can probably and more easily implement such plans as opposed to trying to implement them over a larger and more sprawled area. Those states and their metro areas that have suffered the most casualties per capita from flooding over the decades have typically been South Dakota, Texas, and Colorado (Dittman 1994).

For the reasons mentioned above, this paper puts forth a theory that the greater the urban sprawl or the less the urban compactness in a metro region, the slightly greater the potential for a natural hazards incident occurring in such a region, all else held constant. The probability is only slightly higher given that natural hazards occur with some degree of randomness and in that compactness is not a guarantee to minimize natural hazards. However, due to their compactness, less sprawled regions may avoid some natural hazards than would otherwise be the case. Lambert, Catchen, andVogelgesang (2015) found that FEMA re-building aid was higher on a per capita basis in less compact areas than in more compact ones.

In the course of doing research for this paper, no mention of a theory or set of theories or concept similar to the one advanced in this paper was discovered. In the next section, the methods of analysis are discussed, which is followed by a discussion of the findings. The paper concludes with a discussion and conclusion concerning the results of the analysis and suggestions for further research.

Methods

For the purposes of this paper, urban sprawl is defined as a built environment outside of a central city or central business district characterized by low population and housing density with a lack of mixed land usage (a mingling of commercial and residential structures) and heavy reliance on the automobile for transportation. Such development mostly occurred in the US after the end of the Second World War. Other characteristics of urban sprawl include a high level of racial and income segregation within metro regions with most minorities and poor living in inner city neighborhoods and higher income whites mostly living on the urban fringe in larger sized homes. These are parts of a common definition of urban sprawl used throughout the literature (Mieskowski and Mills 1993, Barnett 1995, Burchell and Lisotkin 1995, Burchell, et al 1998, Ewing 1997, Ciscel 2001, Glaser and Kahn 2003, Wassmer 2008). A sprawl or compactness index was developed by Ewing, Pendall and Chen in 2002 and Ewing and Hamidi in 2014 which measures the degree of sprawl/compactness for urban counties and metro areas. The 2014 index is based on 2010 US Census data and includes variables such as population and housing density per square mile, average block size, employment and commercial location concentration, etc. (Ewing and Hamidi 2014).

Another index used in this paper is from Bert Sperling's Best Places website (http://www.bestplaces.net/), and this index is a measure of risk for natural hazards for residents of metro areas (2011). This "where to live to avoid a natural hazard" index was developed for the *New York Times* and is based upon data from the US National Oceanic Atmospheric Administration (NOAA), US Geological Survey and the University of Miami (http://www.bestplaces.net/docs/studies/safest_places_from_natural_disasters.aspx).[2]

[2] In looking at the maps used in the New York Times piece, one thing that stands out is the low incidence of natural hazards occurring in the Northwest of the United States according to Sperling's Natural Hazards Index. The metro areas of Oregon and Washington state typically have the lowest hazards scores and also incidentally among the lowest sprawl scores according to Ewing and Hamidi (2014).

The association between the Ewing and Hamidi Compactness Index and the Sperling Natural Hazards Index is the main focus of this paper. Since the theory presented in this paper hypothesizes that there is some type of interplay between natural hazards and urban sprawl, least squares regression is employed and is used to predict the Natural Hazards Index of each US metro area using the independent variables of 1) the Compactness Index[3]; 2) the total square miles in size of each metro area in 2010 (US Census Bureau 2010); 3) the change in the number of counties comprising the MSA from 2000 to 2010 (US Census Bureau 2000 and 2010); and 3) a dummy variable where 1 = metro area or the central county of a MSA in the states of Idaho, Oregon or Washington and 0 = metro areas or central counties in other states in the US. The latter variable is used because among the 9 climate regions in the US identified by Karl and Koss (1984), the states of Idaho, Oregon and Washington make up the Northwest Region which has the least variability in weather extremes with regard to tornadoes, earthquakes, and hurricanes. Another dependent variable to be predicted and compared to the results of using the Natural Hazards Index variable is a hazards index created through principal components analysis of some measure of hurricane, tornado, flood, and earthquake incidence in a region over the past few decades. More specifically, the variable is comprised of average annual tornado incidents per 10,000 square miles per state per year, 1991-2010 (US NOAA National Centers for Environmental Information 2015); average flood deaths per capita per state, 1959-1991 (Dittman 1994), a dummy variable for hurricane vulnerability (1 = metro area on Atlantic Coast or Gulf of Mexico, 0 = other) (hurricanescience.org); and a dummy variable for earthquake vulnerability (1 = metro area affected

[3] The Ewing-Hamidi Compactness Index and its previous manifestations are not immune to some criticism. Holcombe and Williams (2010) do not find it to be a good predictor of transportation externalities as Ewing, Pendall and Chen (2002) claim. Interestingly, Holcombe and Williams use both population density and the sprawl/compactness index together in models as predictors of transportation externalities, and yet Appendix B in their paper shows a high degree of correlation between these two variables as would be expected since density is part of the sprawl/compactness index. Holcombe and Williams never really address the issue of possible collinearity between these variables.

by earthquake in last 100 years, 0 = otherwise) (US Geological Survey 2015). For comparison purposes, another model is developed where the same variables are used except that the Compactness Index is replaced with population density per square mile. This is done to show reliability in the index as a measurement of sprawl just as using a hazards index constructed through principal components analysis is used to demonstrate reliability of the Sperling Natural Hazards Index.

Results

(Insert Tables 1, 2 and 3 and Figure 1 around here)

For the Sperling Natural Hazards Index and Compactness Index, 201 metro areas were found to be common to both databases. Table 1 shows the descriptive statistics for the variables used in the analysis. A greater score for the Hazards Index signifies a greater risk of natural hazards incidents in a metro region whereas a greater score for the Compactness Index indicates less sprawl (more compactness) in a metro area. Table 2 shows the correlation matrix for the variables, and the Pearson correlation coefficients do not indicate any possible signs of multicollinearity. Table 3 shows the results of the principal components analysis wherein a natural hazards index independent of the one by Sperling is created and is composed of the four variables mentioned above. The scatter diagram in Figure 1 shows a small but statistically significant relationship between the Sperling Natural Hazards and Compactness indexes, and the correlation matrix in Table 2 also shows some support for the theory put forth in this paper in that there is a mild although statistically significant relationship between the Natural Hazards and Compactness indices. Whether this holds up after controlling for other variables is tested in the regression analysis.[4]

(Insert Table 4 around here)

Table 4 shows the results of different least squares regressions models. In Model 1, the area in square miles of a metro area, an area's Compactness Index score, the change from 2000 to 2010 in the number of counties composing the MSA, and the regional dummy variable are all statistically significant ($\alpha = 0.05$) predictors of the Sperling Natural Hazards Index, although only around 38% of the variation in the Natural Hazards Index is explained by the three variables. The Breusch-Pagan test indicated heteroscedasticity when standard errors are used, and so robust standard errors are used for Model 1. The VIF (variance inflation factor) scores indicate no signs of multicollinearity among the independent variables since each VIF is below 2.0. For a one unit increase in the compactness score, the natural hazards risk score goes down by 0.378 on average whereas a one square mile increase in regional size is associated with around a 0.027 increase in the hazards index on average. A gain of one county to the MSA since the 2000 Census results in a 4.345 increase in the hazards index on average. These findings, therefore, seem to support the contention that more sprawled regions are slightly more prone to natural hazards risk, especially those with larger than average land size or those that have gained land size. Finally, metro areas in the Northwestern states of the US have a hazards index score around 120 points lower than their counterparts in other regions of the US.

In Model 2, the results are similar to those for Model 1 as population per square mile for 2010 is used in place of the Compactness Index to predict the Sperling index. The explanation of

[4] Since neither the Natural Hazards or Compactness index is truncated at zero or a maximum score, the use of Tobit regression in the models is not necessary.

variance is slightly higher for Model 2 at 42%, and population per square mile is statistically significant at $\alpha = 0.05$. A one unit increase in population per square mile is associated with a 0.0177 decrease in the index.

To show some type of reliability or external validity of the previous results, an alternative natural hazards index constructed through principal components analysis and is used as a dependent variable in two additional models using the same independent variables as in Models 1 and 2. Model 3 shows that the independent variables only explain around10% of the variation in the alternative natural hazards index with the Composite Index and region dummy variables statistically significant at $\alpha = 0.05$, and the square miles of a metro area variable significant only at $\alpha = 0.10$, a weaker threshold for avoiding a Type 1 error . In this model, a 1 unit increase in the Compact Index is associated with a 0.007 decrease in the alternative natural hazards index, and metro areas in the Northwestern Climate Region of the US are associated with a lower index score of 0.738 on average and holding all else constant.

Model 4 shows higher adjusted r-squared (30.2%) results when population per square mile is substituted for the Compactness Index. All of the variables are statistically significant at $\alpha = 0.05$ with the exception of the change in number of counties, 2000-10, variable. A one unit increase in population per square mile is associated with a 0.0006 decrease in the alternative natural hazards index, and an increase in one square mile indicates a 0.00059 increase in this index, on average and holding all else constant. Again, metro areas in the Northwestern part of the US have lower natural hazards index scores, this time by an amount 0.733 on average.

Discussion and Conclusion

Future research on this topic would entail trying to find more predictor variables for the dependent variables used in the models in Table 4. Finally, one could look at the increase in the number of FEMA disaster declarations over the last few decades (Lindsay and McCarthy 2015) and try to determine if the amount of sprawl and any increases in the geographic sizes of metro areas have anything to do with the increase in total declarations, although political considerations, weather, and greater sensitivity to the needs of impacted communities may play greater roles in disaster declarations (Haerens and Zott 2013). Nonetheless, as metro areas expand outward, the probability that some part of their land mass is affected by a natural hazard (tornado, flood, storm, or earthquake) could conceivably increase. In that way, with US population and the size of urban areas concurrently increasing, an increase in declarations due to these factors and outside of political and weather related factors is quite possible.

The theory of an influence of urban sprawl on natural hazards that states that a higher degree of urban sprawl exposes a region to a higher probability of natural hazards occurrence is somewhat supported by the regression analysis in the models. However, the explanation of variance for each model is somewhat modest, which is another limitation of this study. Variations in regional US climate appear to play a larger role in natural hazards incidence, yet sprawl or urban compactness and population density appear to play a role along with regional land size or changes in regional land size due to more counties being added. According to the findings of Lambert, Catchen and Vogelgesang (2015), US Federal Emergency Management Agency (FEMA) data show that more sprawled urban counties have higher post-disaster rebuilding costs per capita than less sprawled ones. Therefore, one would expect that if local officials are aware of such costs as well as the increased risk of sprawled areas to natural hazards that future regional development plans would have less of an inclination toward uneven and sprawled development. Tracts of existing urban space could be more intensely developed rather than permitting “leap frog” development in other parts of a metro region. Of course, this all depends upon whether local governments could collaborate enough so as to prevent leap frog development and more sprawl. The fragmentation of local governments within a metropolitan area makes this difficult to do, however. Therefore, sprawled development could continue despite the need for better coordination of regional planning.

Aside from the influence of sprawled development, the ability of local governments to jointly plan for and respond to disasters is already highly fragmented and problematic (Sylves 2015) The possibility that more sprawled areas are at risk of greater natural hazards points to a possible form of bounded rationality when it comes to regional planning. If some risks can be avoided through better urban planning and yet they are not avoided in the future due to a lack of coordinated regional planning and governance, then such behavior is perhaps myopic. That is, by several or many jurisdictions within a metro region each pursuing their own development objectives, the overall welfare of the entire region could suffer through a heightened risk of natural hazards exposure due to poor planning. Additionally, any post hazard re-building is also more expensive on a per capita basis if the research results previously cited are correct. .

For that reason, perhaps natural hazards mitigation through better urban and regional planning is a function best left up to state government or through incentives provided by state governments. For example, the Commonwealth of Kentucky (2013) tries to reduce payouts from the National Flood Insurance Plan, and has as a mitigation action plan that, if resources are available, has as its goals to “prevent or reduce damages to structures through elevation, acquisition, demolition or other flood protection means…” (page 5) and to engage in “voluntary acquisition and demolition of geologically-threatened structures which meet the required benefit and cost analysis, and other requirements of the funding agency, and the restriction of future development on the land. Such projects permanently eliminate damages in the areas of the project" (page 7). If states can work with and help local governments to collaborate in regional hazards mitigation, then one part of the effort could be to promote better regional planning to prevent sprawl since sprawl could raise the risk and costs of natural hazards incidence.

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Table 1: Descriptive Statistics

Variable	Mean	St. Dev.
Natural Hazards Index	173.33	58.14
Compactness Index	100.07	25.32
Chg. Number of Cos.in MSA, 2000-2010	0.54	2.09
Population per Sq. Mile of MSA, 2010	2307.86	932.29
Prin. Comp. Hazards Index	0	1.48
Sq. Miles of MSA	333.2	456.5
Region dummy	0.0597	0.2375

Table 2: Correlation Matrix

	Natural Hazards Index	Compactness Index	Chg. Number Counties.	Pop per Sq. Mile	Principal Comp. Hazards	Sq. Miles	Region Dummy
Natural Hazards Index	1.00						
Compactness Index	-0.29**	1.00					
Chg. Number of Counties	0.22**	-0.37**	1.00				
Pop per Sq. Mile	-0.24**	0.54**	-0.26**	1.00			
Prin. Comp Hazards	0.70**	-0.31**	0.20**	-0.50**	1.00		
Sq. Miles of MSA	0.22**	0.06	-0.11	0.34**	0.11	1.00	
Region Dummy	-0.54**	0.16**	-0.06	0.04	-0.39**	-0.07	1.00

n = 201

**p-value < 0.05
*p-value < 0.10

Table 3: Principle Components Analysis

Eigenanalysis of the Correlation Matrix

Eigenvalue	1.6605	1.0524	0.8020	0.4851
Proportion	0.415	0.263	0.200	0.121
Cumulative	0.415	0.678	0.879	1.000

Variable	**PC1**
Tornado Incident per 10,000 Sq. Miles	0.651
Hurricane Dummy	0.488
Flood Deaths per Capita	0.104
Earthquake Dummy	0.573

Table 4: Linear Regression

Models 1 and 2: Dependent Variable is Sperling Natural Hazards Index

	Model 1		Model 2	
Predictor	**b (Robust SE)**	**VIF**	**b (Robust SE)**	**VIF**
Constant	206.891 (13.697)		206.4 (8.29)	
Sq. Miles	0.0271** (0.059)	1.02	0.038** (0.007)	1.14
Compactness Index	-0.378** (0.126)	1.19		
Chg. Number of Counties	4.345** (1.199)	1.17	4.283** (1.26)	1.07
Region	-119.291** (4.905)	1.03	-121.37** (5.714)	1.01
Pop. Sq. Mile			-0.0177** (0.0031)	1.2
	R-Sq. = 39.02% R-Sq. (adj.) = 37.78%		R-Sq. = 43.25% R-Sq. (adj.) = 42.3%	
	n = 201		n = 201	

**p-value < 0.05
*p-value < 0.10

Models 3 and 4: Dependent Variable is Principal Components Natural Hazards Index

	Model 3		Model 4	
Predictor	**b** **(SE)**	**VIF**	**b** **(SE)**	**VIF**
Constant	0.665 (0.305)		1.12 (0.167)	
Sq. Miles	0.00025** (0.00015)	1.02	0.0006** (0.00014)	1.14
Compactness Index	-0.007** (0.0029)	1.19		
Chg. Number of Counties	0.055 (0.035)	1.17	0.032 (0.029)	1.07
Region	-0.738** (0.287)	1.03	-0.733** (5.714)	1.01
Pop. Sq. Mile			-0.0006** (0.00007)	1.2

R-Sq. = 11.7%   R-Sq. (adj.) = 0.099%

R-Sq. = 31.6%   R-Sq. (adj.) = 30.2%

n = 201

n = 201

**p-value < 0.05
*p-value < 0.10

Figure 1: Scatter Diagram of Compactness Index (X) and Natural Hazards Index (Y)