A SPATIAL EVALUATION OF LABOR MOVEMENTS IN FLORIDA COUNTIES FOLLOWING HURRICANE IRMA

A THESIS

Presented to

The Faculty of the Department of Economics and Business

The Colorado College

In Partial Fulfillment of the Requirements for the Degree

Bachelor of Arts

By

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May 2020

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Mathematical Economics

Abstract

Natural disasters are more frequent and more violent than ever before, while at the same time, the economies of the world are completely interconnected in a global network. This study took both a random effects approach and a spatial lag and spatial error approach to understanding how Hurricane Irma has impacted employment in Florida counties. This study confirms previously found relationships between specific industries and post-disaster growth trends. Concluding, the study finds that displaced workers follow previously existing migration networks when finding new employment after a disaster.

KEYWORDS: (Labor, Disaster, Spatial Lag, Panel Data)

ON MY HONOR, I HAVE NEITHER GIVEN NOR RECEIVED UNAUTHORIZED AID ON THIS THESIS

Signature

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ACKNOWLEDGEMENTS

First and foremost, I would like to thank my advisor, Professor Dan Johnson, for the help and guidance he has provided me through this process. I offer my thanks to the Colorado College and its incredible facility that have invested so much in my education. I would also like thank my parents, for their unending love and support. They are my rock. Finally, I thank my sister, who's sound advice has never led me astray.

INTRODUCTION

Natural disasters and climate change are reshaping the face of the Earth, and with it, reshaping the economics of labor and migration choices. As natural disasters become more unpredictable and volatile, economies and markets that are more resilient to this climate adversity are more desirable. The world and its economies have become globalized, each region interplaying with every other region through a number of facets, to form a web of network interactions. This study attempts to account for some of those network effects through the use of an Exploratory Spatial Weighting methodology using migration history as the measure of closeness With the increasing prevalence and degree of devastation resulting from climate disasters, it is ever more important to thoroughly study the intersection of climate, space, and labor economics, finding what is successful and what can be emulated.

Natural disasters are increasingly prevalent and severe, fueled by rising sea temperatures and erratic weather patterns that are attributed to global warming. From 1987-2007, the annual number natural catastrophizes doubled, from 200 to 400[1]. Flashing forward a decade, 2017 recorded 710 such events, which was above the last decade’s average of 605 events[2]. Harmful weather events are becoming more common, and more

[1] United Nations. (n.d.). UNHCR Policy Paper: Climate change, natural disasters and human displacement: a UNHCR perspective. Retrieved from https://www.unhcr.org/4901e81a4.html).

[2] Löw, P. (2018, January 4). Hurricanes cause record losses in 2017 - The year in figures: Munich Re. Retrieved from https://www.munichre.com/topics-online/en/climate-change-and-natural-disasters/natural-disasters/2017-year-in-figures.html

severe. Of those 710 events, Hurricanes Harvey, Irma and Maria are among the most powerful and costly disaster to ever hit the United States. Hurricane Irma was the most powerful hurricane ever recorded when it made landfall in Barbuda on September 6th of 2017, have maintained windspeeds of over 185 miles per hour for 37 hours[3]. The storm was able to maintain this ferocity for such a duration due to the above average sea temperatures[4].

Natural disasters take a severe and long-lasting economic toil on the areas they impact. In 2017, North America, Central America and the Caribbean suffer an estimated overall loss of US$ 280 billion due to natural disasters, of which only US$ 128 billion was insured[5]. Of natural disasters, hurricanes and their aftermaths tend to be the most economically devasting. The majority of the United States economy can be found in coastal regions, with 50% of our population and 57% of the national income finding home there[6]. Thus, the US's most vibrant cities and largest economies repeatedly suffer costly damage to capital. Hurricanes Harvey, Irma, and Maria, all hitting the US mainland in 2017, are estimated to have collectively caused US$ 265 billion dollars of

[3] Amadeo, K. (2019, October 21). Hurricane Irma Damage Was $50 Billion. Retrieved from https://www.thebalance.com/hurricane-irma-facts-timeline-damage-costs-4150395

[4] Hot water ahead for Hurricane Irma – Climate Change: Vital Signs of the Planet. (2017, September 7). Retrieved from https://climate.nasa.gov/news/2625/hot-water-ahead-for-hurricane-irma/

[5] Löw, P. (2018, January 4). Hurricanes cause record losses in 2017 - The year in figures: Munich Re. Retrieved from https://www.munichre.com/topics-online/en/climate-change-and-natural-disasters/natural-disasters/2017-year-in-figures.html

[6] Myers, A. (2018, January 5). What the 2017 hurricane season can teach us about disaster preparedness and city planning. Retrieved from https://hub.jhu.edu/2018/01/05/business-economics-of-natural-disasters/

damage[7]. Hurricane Irma, which cost the US an estimated US$ 50 billion, did not directly hit Miami. If it had, cost projections estimate the hurricane would have destroyed US$ 300 billion worth of property. The costs of disaster damages are direct and indirect, with hidden impacts that can slow growth for years to come. Although, certain sectors can see profits from the rebuilding effort, the inefficiency of these repeated losses is financially draining for those impacted[8]. The burden of hurricanes is not isolated to coastal areas. The disasters cause displacement of coastal residents, increasing job competition inland, lowering wages, and increasing housing prices. The loans required to rebuild damaged areas can limit credit access all over the country, stymying growth.

In this era of globalized economics, production and supply are dominated by intercontinental networks, and labor is no different. Globalized and interconnected, the labor force has easy access to travel and can greatly impact how firms and workers compete and adapt under stresses such as hurricanes. Traditional spatial applications, using contiguity or inverse distance are not necessarily sufficient in capturing these movements of labor. Existing diaspora and unseen barriers restrict the validity of neighbor and distance based spatial approaches, lending support to a migratory based approach to spatial specification.

7 Amadeo, K. (2019, November 20). Natural Disasters Are a Bigger Threat Than Terrorism. Retrieved from https://www.thebalance.com/cost-of-natural-disasters-3306214

8 Chris Mooney, B. D. (2018, January 8). Extreme hurricanes and wildfires made 2017 the most costly U.S. disaster year on record. Retrieved from https://www.washingtonpost.com/news/energy-environment/wp/2018/01/08/hurricanes-wildfires-made-2017-the-most-costly-u-s-disaster-year-on-record/?wpisrc=nl_energy202&wpmm=1).

LITERATURE REVIEW

Disasters interfere with businesses in a variety of ways. Direct physical destruction of firm capital creates temporary setbacks, while destruction of shared capital such as transportation infrastructure, telecommunications, water, and power can impact business long into the disaster aftermath[9]. Of course, these damages impact sectors differently, some even showing growth. Wholesale and retail industries report heavy losses following disaster, while manufacturing and construction often will show gains[10]. Lee (2018) found that in Aransas county, Texas, Hurricane Harvey had negative effects on retail a year later while construction, education, real estate, finance and insurance were strongest to recover, re-enforcing previous literature's findings[11].

The term resilience is popular among the social sciences and therefore can hold varying definitions depending on the context. For example, in environmental and ecological studies, resilience describes the "capacity to adapt and thrive under adverse environmental conditions," which ultimately provides a strong base from which we build our understanding of economic resilience[12]. Economic resilience is the ability to return to

9 Zhang, Y., Lindell, M. K., & Prater, C. S. (2008, May 22). Vulnerability of community businesses to environmental disasters. Retrieved from https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1467-7717.2008.01061.x

10 Kroll, Cynthia, Landis, John, Shen, Sean, & Stryker. (2012, July 25). The Economic Impacts of the Loma Prieta Earthquake: A Focus on Small Business. Retrieved from https://escholarship.org/uc/item/6s67g8mh

11 Lee, J. (2018, December 5). Business recovery from Hurricane Harvey. Retrieved from https://www.sciencedirect.com/science/article/pii/S2212420918309683

12 Christopherson, S., Michie, J., & Tyler, P. (2010). Regional resilience: theoretical and empirical perspectives. *Cambridge Journal of Regions, Economy and Society* . Retrieved from https://pdfs.semanticscholar.org/ea5e/2727b52bfb159fbfe6e5aba50360a7b6aaeb.pdf

and remain near the pre-shock equilibrium. Huang (2017) frames this as performance and capacity. Xiao and Drucker (2013)[13] use similar definitions of resilience, emphasizing both recuperating and sustaining pre-shock growth trends.

Resilience can also be framed in terms of path dependence. Resilience economies better able to avoid being "locked-in" to inefficient equilibria and instead can find the optimal, or at least better, equilibrium[14]. In the context of natural disasters, the 1927 Great Mississippi flood forced agricultural landowners to mechanize their production function due to the mass out-migration of the work force. In this case, this change in labor equilibrium was the result of an exogenous shock, not the economies inherent resilience to path dependence. However, a similar mechanization effect took hold of the rest of the American South in 1940-1970, with the large-scale exodus of the black agricultural labor force. Migration plays an important role in economies' ability to self-regulated and, in this case, promote structural economic development[15].

When examining regional resilience, it is tempting to engage with regions as independent actors. However, each region is a part of a political and economic spatial network. Trade and regulatory policies can drive local development or the decline of

[13] Xiao, Y., & Drucker, J. (2013). Does Economic Diversity Enhance Regional Disaster Resilience? *Journal of the American Planning Association, 79*(2), 148–160. doi: 10.1080/01944363.2013.882125

[14] Hill, Edward; Wial, Howard; Wolman, Harold (2008) : Exploring regional economic resilience, Working Paper, No. 2008,04, University of California, Institute of Urban and Regional Development (IURD), Berkeley, CA

[15] Hornbeck, R. (n.d.). WHEN THE LEVEE BREAKS: BLACK MIGRATION AND ECONOMIC DEVELOPMENT IN THE AMERICAN SOUTH. *NBER Working Paper*. Retrieved from https://www.nber.org/papers/w18296.pdf

specific industries[16]. Individuals' decision making incorporates the opportunities and risks of other regions. Thus, it seems that accounting for the spatial and connective relationship between regions is necessary.

Tracking business recovery in Katrina, many businesses that were initial able to reopen had failed a year later[17][18]. This is in part reflective of the pre-disaster economic difficulties already afflicting New Orleans. Economies in decline fall further and recover slower than those experiencing growth. Population dislocation coupled with slow return can be particularly crippling for small businesses which rely on habitual patronage. Small businesses experience higher rates of failure and have a harder time returning to pre-disaster growth rates[19][20]. Xi Huang's 2017 study of economic resilience argues that immigrant populations, and the small business associated with them, can build resilience capacity through their meso contributions to civic organization and their entrepreneurism. Greater numbers of immigrants correspond to greater numbers of community

16 Christopherson, S., Michie, J., & Tyler, P. (2010). Regional resilience: theoretical and empirical perspectives. *Cambridge Journal of Regions, Economy and Society* . Retrieved from https://pdfs.semanticscholar.org/ea5e/2727b52bfb159fbfe6e5aba50360a7b6aaeb.pdf

17 Schrank, H. L., Marshall, M. I., Hall-Phillips, A., Wiatt, R. F., & Jones, N. E. (2012). Small-business demise and recovery after Katrina: rate of survival and demise. *Natural Hazards*, *65*(3), 2353–2374. doi: 10.1007/s11069-012-0480-2

18 Sydnor, Sandra & Niehm, Linda & Lee, Yoon & Marshall, Maria & Schrank, Holly. (2016). Analysis of post-disaster damage and disruptive impacts on the operating status of small businesses after Hurricane Katrina. Natural Hazards. 85. 10.1007/s11069-016-2652-y.

19 Arendt, Lucy & Alesch, Dan. (2009). Managing for long-term recovery in the aftermath of disaster.

20 Zhang, Y., Lindell, M. K., & Prater, C. S. (2008, May 22). Vulnerability of community businesses to environmental disasters. Retrieved from https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1467-7717.2008.01061.x

organizations that bolster disaster response capacity and serve as a network for reintegration into the workforce. High numbers of immigrants also are associated with greater numbers of small businesses that, during a shock, can be more adaptive and innovative. This finding does not accord with the majority of literature on small businesses. Thus, it seems that Huang's 2017 finding speaks more to the connectivity of immigrant networks, rather than the small businesses themselves[21].

While specialization does contribute to efficient production, it also creates vulnerability in the local economy. Diversity of industry includes "redundancy of functions," spreading the risk of a shock across firms and sectors. On the micro level, economically diverse regions increase the likely hood that skills will be transferable, thus contributing to employment recovery[22]. Among the most important factors to bolster resilience are a skilled and entrepreneurial workforce and a diversified economy that is not overly dependent on a single sector[23]. The investigation and the approach taken in this study was inspired in part by Xiao and Drucker's 2013 evaluation of the role economic diversity plays in disaster resilience. Their study of the 1993 U.S. Mid-West

21 Huang, Xi, "Immigration, Regional Resilience, and Local Economic Development Policy." Dissertation, Georgia State University, 2017. https://scholarworks.gsu.edu/pmap_diss/69

22 Yu, & Xuewei. (2015, August 1). Interconnections between regional industrial structure and energy consumption patterns. Retrieved from https://smartech.gatech.edu/handle/1853/53853

23 Christopherson, S., Michie, J., & Tyler, P. (2010). Regional resilience: theoretical and empirical perspectives. *Cambridge Journal of Regions, Economy and Society* . Retrieved from https://pdfs.semanticscholar.org/ea5e/2727b52bfb159fbfe6e5aba50360a7b6aaeb.pdf

flood found that economically diverse counties recovered employment and income faster following the flood, out-performing their less-diverse counterparts.

Belasen and Polachek (2009)[24] implement a generalized difference-in-difference technique that adapts a standard DD model to compare many test groups and many control groups across multiple treatment events. This design benefits the study by allowing for different types of treatment (in this case intensity of hurricane) and different characteristics in the groups. In addition, this study used a dummy matrix to capture the "neighboring effect" of out-migration from directly impacted counties to neighboring counties. Labor theory indicates that counties directly hit by hurricanes will see a decrease in employment followed by an increase in earnings, as the labor supply shifts inwards. The reverse relationship can be expected from neighboring counties, which receive the new labor and therefore should see lower wages. However, in this study earnings of neighboring counties fell despite statistically insignificant change in employment. This effect is explained by Belasen's and Polachek's previous 2008 study, finding higher earning residents of neighboring counties leave for a great level of safety, lowering the earnings composition. When evaluated time delayed effects of a storm, it is possible that the effect is mitigated by a second storm that closely follows within that same period[25].

24 Belasen, A. R., & Polachek, S. W. (2012, April 4). How Disasters Affect Local Labor Markets: The Effects of Hurricanes in Florida. Retrieved from https://muse.jhu.edu/article/466694/pdf

25 Ewing, B. T., Kruse, J. B., & Schroeder, J. L. (2005, September 1). Time series analysis of wind speed with time-varying turbulence. Retrieved from https://onlinelibrary.wiley.com/doi/epdf/10.1002/env.754

THEORY

LABOR

Labor and disaster economic theory intersect to build a basis for a theoretical understand of how employment shifts during a natural disaster. Areas directly impacted by a natural disaster experiences an exodus of labor and with that shortage of labor, wages shifts up in response. Surrounding regions absorb the influx of labor, and experience a corresponding drop in wages. Once the danger of the disaster subsides, labor shifts back into the impacted areas, and wages creep down, eventually finding a new equilibrium. There is potential that hidden factors, such as unseen barriers and meso effects, can dilute this effect.

VARIABLE JUSTIFICATION

Below, equation 3.1, shows the core variables repeatedly used throughout this study. These variables serve to effectively predict employment, while also studying what makes economies and regions more or less resilient to natural disasters and shocks in general. This subjection is dedicated to covering the supporting literature and a priori that justify each variable.

Core Model: (3.1)

$$\text{Employ} = \beta 1 \text{ industrywage} + \beta 2\text{diverse} + \beta 3\text{connect} + \beta 4\text{industryGDP}$$

The use of employment in this model requires little explanation, as it is the subject matter of this study. The progression of employment levels over time can be a powerful indicator of economic growth. The first explanatory variable, industrywage, is the Average Annual Wage per industry per county in US dollars. Wages drive employment levels and are central to all personal optimization decisions that are made on a micro scale. Wage also serves as the base variable, explaining a bulk of the variance of employment levels. The variable diverse is an index measuring diversity of industry through Herfindahl-Hirschman that is calculated by summing the squares of each industries % of total employment. For this index, values closer to one, indicate that employment in that county is dominant by a single industry. Such dominance of industry cause vulnerability as it can eliminate redundancy of systems and opportunities for skill transfers[26]. Further support diversity as a critical feature of economic resilience was Xiao and Drucker's 2013 study of county resilience following major flooding, in which they found diverse counties were less effected and faster to recover than their less diverse counterparts[27]. The variable connect operates as an index of connectivity. It measures average net migration between the county and every other Florida county. Xi Huang's 2017 study of economic resilience argued that connectivity and meso effects of migrant networks can bolster economic resilience. Finally, the variable industryGDP contains observations of the GDP of each industry in each county. This variable contributes to controlling for previous economic trends, contextualize results.

26 Yu, & Xuewei. (2015, August 1). Interconnections between regional industrial structure and energy consumption patterns. Retrieved from https://smartech.gatech.edu/handle/1853/53853

27 Xiao, Y., & Drucker, J. (2013). Does Economic Diversity Enhance Regional Disaster Resilience? *Journal of the American Planning Association*, *79*(2), 148–160. doi: 10.1080/01944363.2013.882125

SPATIAL THEORY

Determining if a spatial approach is appropriate requires consideration of what imposing a spatial factor would mean for your data and analysis, as well as econometric testing to determine if, indeed a spatial approach is required. The basic assumption of both random effect and fixed effect models is that observations are of individuals are independent of one another. However, given that individuals are counties that coexist within the same geographical area that assumption cannot be accepted.

A simple approach, such as an OLS regression, to data that is geographically related may be largely insufficient as it fails to account for the impact between nearby regions. Thus, this study of Florida counties must test for this spatial correlation. Walder Tobler famously established the first law of geography, that “Everything interacts with everything, but two nearby objects are more likely to do so than two distant objects.” Taken to heart, standard procedure for Spatial economic evaluation relates objects through either contiguity or distance. A matrix is established that weights the proximity of objects, in binary to indicate contiguity or with the inverse of the distance between them. This study takes on an untraditional approach for weighting these distances. Using net county to county migration counts from 2012-2016 (the time frame immediately preceding our period of study) the connectivity between counties is measured in movement of people. The a priori of these method is grounded in the modern status of globalization, in which physical proximity does not imply the highest degree of connectivity. In addition, if physical proximity persists as an important factor, the migratory data encompasses that effect. Admittedly, the rational for this type of weighting system exposes a limitation of the same kind. The state of Florida and it’s counties are not an isolated system and the migration of people extends far beyond the county to county level. While this study is focused in the spatial interactions found on the county level, the standard errors presented here are liberal as the study fails to account for interactions occurring outside of Florida. To exemplify this issue, consider the case of Caribbean islands such as Cuba, or Puerto Rico. During Hurricane Irma for Cuba, and Maria for Puerto Rico, wide spread destruction of structures on the island displaced thousands of people, many of whom ended up in Florida, particularly in Miami. This study does not take non-intercounty migrations into account.

DATA SECTION

DESCRIPTION

Observations on Income and on GDP per industry were sourced from the Bureau of Economic Analysis[28]. Population counts for counties are found in the University of Florida's Bureau of Economic and Business Research[29]. Labor and Wage data, which form the bulk of the set, are sourced from Florida Jobs, Quarterly Census[30]. To form the spatial weighting matrix, county-to-county net migration flows from 2012-2016 were pulled from the US Census[31].

Below in Table 1, the descriptive statistics of the core variables are presented. GDP by industry has the fewest observations at 17616, and thus will be the limiting variable of the regressions. Employment and Connectivity Index are measured in people employed. Both Average Annual Wage by Industry and GDP by Industry are measured in US$. Finally, the HH-Diversity Index is calculated by summing the squares of each industries % of total employment.

28 GDP by Industry. (n.d.). Retrieved from https://www.bea.gov/data/gdp/gdp-industry

29 University, F. (n.d.). Florida Estimates of Population. Retrieved from https://www.bebr.ufl.edu/sites/default/files/Research Reports/estimates_2018.pdf

30 Quarterly Census of Employment and Wages. (n.d.). Retrieved from http://www.floridajobs.org/workforce-statistics/data-center/statistical-programs/quarterly-census-of-employment-and-wages

31 US Census Bureau. (2018, November 15). County-to-County Migration Flows: 2012-2016 ACS. Retrieved from https://www.census.gov/data/tables/2016/demo/geographic-mobility/county-to-county-migration-2012-2016.html

Table 1.
Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Employment	18684	17928.86	74763.06	6	1170000
AvgAnnualWage by Industry	18684	44738.41	14916.85	7641	155000
Connectivity Index	19296	81.525	86.002	9.776	484.567
HH-Diversity	19296	.066	.019	0	.197
GDP by Industry (dollars)	17616	2533.769	10126.45	.161	165000

To confirm that these variables are viable to use together, correlation among the explanatory variables is tested. The study finds no autocorrelation among the independent variables, as seen in the correlation matrix in Table 2.

Table 2.
Matrix of correlations

Variables	(1)	(2)	(3)	(4)
(1) nAvgAnnualWage~y	1.000			
(2) ConnectivityIn~x	0.342	1.000		
(3) HHDiversity	-0.032	-0.046	1.000	
(4) GDPbyIndindoll~s	0.144	0.419	-0.044	1.000

RANDOM EFFECTS MODEL

The data was then xtset on the account it is panel data. There are two panel variables, county and industry, thus a combined identification variable was created to specify the xtset. Using Hausman's 1978 test for model specification, seen in Table 3, the null hypothesis, that a random effects model is appropriate, is failed to be rejected with a chi-squared value of -1.72. This indicates that the unique errors are not correlated with the regressors of the model. The random effects model aligns with the expectations of the model, as each industry can be considered random and a subset of the total population of all industries.

Table 3.
Hausman (1978) specification test

	Coef.
Chi-square test value	-1.72
P-value	1

Ensuring the model will be econometrically sound, the residuals were regressed against the lag of the residuals and the lag of the lag of the residuals. No higher order serial correlation was found for this model. The complete random effects model is shown below, in equation 4.1.

Random Effects Model: (4.1)

$$Employ = \beta_1 connect + \beta_2 diverse + \beta_3 industryGDP + \beta_4 industrywage + \beta_5 dSep2017 + \beta_6 dSepOct2017 + \beta_7 dSepOctNov2017 + \beta_8 dHitDirect + \beta_9 dHurricane + \beta_{10} dNeighbor + \beta_{11-21} industrydummies_{1-11} + \varepsilon$$

Figure 1.

Variables List:

Employ: number of people employed per industry per county

Connect: Connectivity Index measuring average net migration between the county and every other Florida county

Diverse: Herfindahl-Hirschman index calculated by summing the squares of each industries % of total employment, values closer to one indicate greater dominance of a single industry

IndustryGDP: GDP by industry by county

IndustryWage: Average Annual Wages by industry by county

dSep2017: dummy variable with 1 values for September of 2017 *dSepOct2017*: dummy variable with 1 values for September and October of 2017

dSepOctNov2017: dummy variable with 1 values for September, October, and November of 2017

dHitDirect: dummy variable with 1 values for directly hit counties as specified by the National Weather Service

dHurricane: dummy variable with 1 values for all counties from September (hurricane landfall) through the end of 2018

dNeighbor: dummy variable with 1 values for all counties that share borders with *dHitDirect* counties

industrydummies: dummy variables with 1 values indicating which industry observations are assigned to, industry NAICS Code numbers and names below

11. Agricultural, Forestry, Hunting & Fishing
23. Construction
31. Manufactoring
42. Wholesale Trade
44. Retail Trade
48. Transportation & Warehousing
51. Information
54. Professional & Technical Services
56. Administration & Waste Services
62. Health Care & Social Services
1023. Financial Activities

SPATIAL

This sections services to make clear the spatial components of the data set, the econometric testing of spatial modeling, and the ultimate spatial model chosen.

Below is a subsection of the spatial weight matrix (Table 4), using the counties Alachua, Baker, Bay, Bradford, and Brevard. The full matrix follows the same structure, encompassing every county from Alachua to Washington, forming a 67x67 matrix. The first column and row indicate the FIPS county identification number. The second column and row contain the county name. The remainder of the subsection is the spatial weighting matrix. The cross section of Alachua and Baker indicates that the net migration between the two counties from 2012-2016 was 59 people. The matrix is symmetric, meaning that the values do not have direction, they only indicate the degree of connectivity. The diagonal, indicating a counties connectivity with itself, is the population of the county in 2016. By using population of the county, the degree of connectivity becomes relative to the size of the county, while maintain consistency of the units used.

Table 4.

		001	**003**	**005**	**007**	**009**
		Alachua	**Baker**	**Bay**	**Bradford**	**Brevard**
001	**Alachua**	257062	59	272	31	129
003	**Baker**	59	26965	246	32	6
005	**Bay**	272	246	176016	7	630
007	**Bradford**	31	32	7	27440	1
009	**Brevard**	129	6	630	1	568919

To make the weighting matrix useful, it must be expanded to the same dimensions as the explanatory variables. This means that the entire matrix has 67x12x24 rows and columns for counties times industries times months, respectively. Ultimately, however the spatial matrix and analysis are downsized in this study, due to inadequate modeling software and machine power. Thus in the spatial modeling discussed later, an eleven month subsection, June 2017 to April 2018, was taken to capture the critical time surround Hurricane Irma. The scope needed downsizing with respect to the industries, therefore the study evaluates the All Industries totals. All said and done, the final weighting matrix is 67 counties by 11 months by 1 industry, 737x737.

To determine which type of spatial model is appropriate, econometric testing must be conducted on our data set. Below in Figure 2, are the results of the diagnostic test for spatial autocorrelation in the error terms and the lags of X variables. Evaluating the Robust Lagrange multiplier, we reject the null hypothesizes that there is no autocorrelation for both the error terms and the lags of explanatory variables. Indicating both a Spatial Error Model (SEM) and a Spatial Lag of Explanatory Variables model (SLX) are appropriate. The SEM is similar to the random effect model in that it is assumed that the individual effects within a region are similar and the fixed effects cannot be estimated. The SLX model accounts for the exogenous interactions of the explanatory variables.

Figure 2.
Diagnostic tests for spatial dependence in OLS regression
Fitted model

nEmploy = nAvgAnnualWagesbyIndustry + HHDiversity + GDPbyIndindollars + dNeighbor + dHurr + dHitDirect

Weights matrix

Name: elevenMat
Type: Imported (non-binary)
Row-standardized: No

Diagnostics

Test	Statistic	df	p-value
Spatial error:			
Moran's I	0.565	1	0.572
Lagrange multiplier	19000.000	1	0.000
Robust Lagrange multiplier	19000.000	1	0.000
Spatial lag:			
Lagrange multiplier	268.528	1	0.000
Robust Lagrange multiplier	442.378	1	0.000

Having determined that a Spatial Error Model is appropriate, the theoretical spatial model can be applied to this set. The model, seen in equations 4.2a and 4.2b below, incorporates the weighting matrix into the error term. The error term of the model, u_{ic} can be defined as a constant α_i plus the error terms u_{ij} of the other counties scaled by the weighting matrix W, plus the ε_i error term that is approximately an independent and identically distributed random variable. The errors, u_{ic} and u_{ij} have subscripts *i, c,* and *j,* indicating industry *i,* and county, *c* and *j*. These subscripts are such that c is not equal to j, thereby making the errors of county *c* a function of the weighted errors of county *j*. Of the explanatory variables, connect is no longer included. Connect uses the same data used in the spatial weighting matrix to build an index of connectivity for each county. In both the SEM and SLX models this variable is not needed as the connectivity of counties is controlled for spatially.

SEM (4.2a)

$$Employ_{ic} = \beta 2diverse_{ic} + \beta 3industryGDP_{ic} + \beta 4industrywage_{ic} + \beta 8dHitDirect_{ic} + \beta 9dHurricane_{ic} + \beta 10dNeighbor_{ic} + u_{ic}$$

$$u_{ic} = \alpha_i + \lambda W u_{ij} + \varepsilon_i \text{ , where c does not equal j} \quad (4.2b)$$

Similarly to the SEM model, the SLX model adds the weighting matrix term to the equation, however in this case the W matrix is scaling the explanatory variables. The model, seen below as equation 4.3, has terms βX for each variable as well as terms θWX for each variable. The ε_i error term here is not spatially weighted and is an independent and identically distributed random variable.

SLX (4.3)

$$\text{Employ}_{ic} = \beta_1\text{diverse}_{ic} + \beta_2\text{industryGDP}_{ic} + \beta_3\text{industrywage}_{ic} + \beta_4\text{dHitDirect}_{ic} + \beta_5\text{dHurricane}_{ic} + \beta_6\text{dNeighbor}_{ic} + \theta_1\text{Wdiverse}_{ic} + \theta_2\text{WindustryGDP}_{ic} + \theta_3\text{Windustrywage}_{ic} + \theta_4\text{WdHitDirect}_{ic} + \theta_5\text{WdHurricane}_{ic} + \theta_6\text{WdNeighbor}_{ic} + \varepsilon_{ic}$$

Both the SEM and SLX models must be evaluated to understand how the spatial component impacts results.

DATA ANALYSIS

RANDOM EFFECTS ANALYSIS

Below, in Table 5, are the regression results of the random effects xt model of equation 1.1. The Connectivity Index is found to be significant on the 1% level, with a t-value of 42.48. The coefficient of 318.375 indicates that every 1 person increase in the average net migration with every other county corresponds to 318.375 higher employment in the county. The Average Annual Wages by Industry is significant on the 5% level, and has a coefficient of 0.017. This signifies that a dollar increase in the average annual wage by industry is tied to a 0.017 greater employment per industry. Multiplying for a more digestible scale, finds that a US$ 58.82 increase in average annual wage corresponds to 1 more person employed per industry. HHDiversity, which indicates the composition of industry dominance within a county as a measure of the counties diversity, was found to be insignificant. As this study has discussed, relevant literature indicates that a diverse composition of industries can be critical to healthy economies, however here, the results are inconclusive. GDP by Industry (US$) is significant on the 1% level, with a t-value of 27.18. A one dollar increase in GDP by Industry corresponds to 0.352 more people employed per industry.

The dummy variables included in this study serve to build understanding of the impact Hurricane Irma had on employment in different time periods, industries and groupings of counties. The dummy dSep2017 is September of 2017, which is when Hurricane Irma tracked through Florida and is the first time period in which the hurricane has an impact. This dummy is significant to the 1% level, with a coefficient of -567.046.

During September of 2017, 567 fewer people per industry were employed than were in the rest of 2017 and 2018. Continuing along the timeline, the dummy dSepOct2017 controls for the months of September and October of 2017. Significant on the 1% level, 285.378 fewer people per industry were employed than were in the rest of the time period. However, the next dummy, dSepOctNov2017, is not significant. Collective employment in the months September, October, and November of 2017 were not significantly different than the rest of the time period.

Dummy dHitDirect, which indicates the counties that are considered to have been within the direct path of Hurricane Irma is significant to the 10% level. The coefficient of 117.186 suggests that counties directly hit by the hurricane employed 117.186 more people per industry in the period following the hurricane than those that were not hit, or had not yet been hit. This coefficient can be explained in a few ways. During the period following a disaster, there is often an influx of temporary medical, construction, and social workers, tasked with aiding the recovery and rebuild of the impacted area. These workers may artificially inflate employment numbers for a time. In addition, this coefficient indicates that the directly hit counties are growth areas, as the growth of employment overcame the setback demonstrated by the September 2017 dummy. Taking a look at an interaction between dSep2017 and dHitDirect finds a coefficient of -997.37 people employed per industry, significant at the 1% level. This interaction term supports the theory that directly hit counties see high loss of employment during the disaster. This further supports the theory that economic growth of these counties was able to resurge, with employment losses regained and surpassing the pre-hurricane levels. The variable dNeighbor codes whether a county shared a border with a county directly hit by

Hurricane Irma. The neighboring county dummy, significant on the 5% level, specifies 3674.101 more people employed per industry per county, as compared to counties that did not neighbor a directly hit county. This coefficient supports the labor theory that the people displaced by the storm find employment in the neighboring areas. Looking at the interaction between September of 2017 and the neighbor county dummies, it is clear that neighboring counties experienced displacement of people and jobs as well, with a coefficient of -417.386, significant at the 10% level. Given the size of Hurricane Irma, as well as the unpredictability of storm paths, it is not surprising that neighbor counties were evacuated and people were displaced. However, the 3674 more people employed per industry in those counties suggests that residents were able to return and regain employment more quickly, and that displaced people in the directly hit counties were able to find employment in those neighboring counties. The final time dummy controls for the time period after Hurricane Irma had hit, from September 2017 through the end of 2018. Significant at the 1% level, the coefficient of dHurr indicates that during the period after the hurricane hit, 458.373 more people were employed per industry per county, as compared to the time period before the hurricane. Similarly with dHitDirect, this coefficient is evidence that Florida counties remain a growth area despite being hit by Hurricane Irma, and have surpassed their pre-hurricane employment levels. This study does not determine how these employment levels compare to projected employment levels for these groups.

Table 5.

XT Random Effects Regression results

nEmploy	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
ConnectivityIndex	318.375	7.495	42.48	0.000	303.686	333.065	***
AvgAnnualWagesbyInd	0.017	0.008	2.21	0.027	0.002	0.032	**
HHDiversity	100.526	3120.765	0.03	0.974	-6016.062	6217.113	
GDPbyIndindollar	0.352	0.013	27.18	0.000	0.326	0.377	***
dSep2017	-567.046	107.072	-5.30	0.000	-776.903	-357.190	***
dSepOct2017	-285.378	107.078	-2.67	0.008	-495.247	-75.510	***
dSepOctNov2017	-18.716	79.627	-0.23	0.814	-174.782	137.350	
dHitDirect	117.186	68.925	1.70	0.089	-17.904	252.277	*
dNeighbor	3674.101	1724.215	2.13	0.033	294.702	7053.500	**
dHurr	458.373	44.568	10.29	0.000	371.021	545.724	***
10b.NAICSCode	0.000	.	.	.	.	.	
11. Agr., Hunting	-119000.000	3199.916	-37.05	0.000	-125000.000	-112000.000	***
23.Construction	-112000.000	3133.273	-35.68	0.000	-118000.000	-106000.000	***
31.Manufactoring	-115000.000	3159.585	-36.30	0.000	-121000.000	-108000.000	***
42.Wholesale Trade	-116000.000	3160.765	-36.66	0.000	-122000.000	-110000.000	***
44.Retail Trade	-103000.000	3110.988	-32.95	0.000	-109000.000	-96400.000	***
48.Transport. & Warehousing	-115000.000	3120.609	-37.00	0.000	-122000.000	-109000.000	***
51.Information	-120000.000	3229.891	-37.22	0.000	-127000.000	-114000.000	***
54.Professional & Technical Services	-112000.000	3122.680	-35.93	0.000	-118000.000	-106000.000	***
56.Admin. & Waste	-111000.000	3186.046	-34.79	0.000	-117000.000	-105000.000	***
62.Health Care & Social	-102000.000	3133.195	-32.43	0.000	-108000.000	-95500.000	***
1023.Financial Activities	-112000.000	3120.722	-35.94	0.000	-118000.000	-106000.000	***
Constant	91297.150	2325.889	39.25	0.000	86738.491	95855.809	***

Mean dependent var	19256.828	SD dependent var	77418.867
Overall r-squared	0.405	Number of obs	17352.000
Chi-square	5754.227	Prob > chi2	0.000
R-squared within	0.048	R-squared between	0.405

**** p<0.01, ** p<0.05, * p<0.1*

Finally, dummies were constructed for each of the 11 industries included in this study. Results are with respect to the All Industry Total, hence the negative coefficients for each specific industry, as they only account for a part of the Total. Below in Table 6, are the results for an interaction between each industry and the directly hit dummy. All terms are significant to the 1% level. These results reveal that employment levels in Construction, Health Care and Social Services, Professional and Technical Services, and

Financial Activities had employment levels closer to those industries in counties not directly hit. This relationship is expected and supported in the relevant literature. Construction, professional, and technical workers are needed for the rebuild effort and should be among the first to return to and be rehired in the directly impacted areas. Health Care and Social Service workers are also among the first to return, with their work being crucial following the crisis of a hurricane. Industries furthest from the employment levels of those not directly hit by the hurricane, are the Agricultural, Forestry, Fishing and Hunting, Manufacturing, Whole Sale Trade, Retail Trade, Information, Administration and Waste services, and most of all Transportation and Warehousing. Many of these industries are reliant upon capital for their success. Agricultural lands and crops devastated by hurricane floods and winds result in low employment. Fishing boats, ferries, and buses are destroyed eliminating jobs in fishing and transportation. Trade and manufacturing respond to the anticipated drop in demand that follows disasters and are slower to rehire workers. The slower response from Information industries is less clear. There are some indications that Information industries should be more adaptable to disasters, as they are able to work remotely and have minimal risk to capital. However, an argument could be made that the Information industry is positioned to continuing operating with a reduced staff, and requires fewer staff members to begin with, explaining its low employment level.

Table #.
dHitDirect interaction with Industry Regression results

nEmploy	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
.							
.							
dHitDirect#Industry							
11. Agr., Hunting	-3763.730	260.735	-14.44	0.000	-4274.762	-3252.699	***
23.Construction	-2905.539	260.664	-11.15	0.000	-3416.431	-2394.646	***
31.Manufactoring	-3435.177	265.167	-12.96	0.000	-3954.895	-2915.459	***
42.Wholesale Trade	-3252.769	264.021	-12.32	0.000	-3770.240	-2735.298	***
44.Retail Trade	-3332.550	261.904	-12.72	0.000	-3845.873	-2819.227	***
48.Transport. & Warehousing	-4585.863	269.043	-17.05	0.000	-5113.177	-4058.549	***
51.Information	-3845.119	266.422	-14.43	0.000	-4367.297	-3322.942	***
54.Professional & Technical Services	-2896.349	264.642	-10.94	0.000	-3415.037	-2377.661	***
56.Admin. & Waste	-3349.266	271.747	-12.32	0.000	-3881.881	-2816.651	***
62.Health Care & Social	-2615.400	267.788	-9.77	0.000	-3140.254	-2090.545	***
1023.Financial Activities	-2645.376	265.990	-9.95	0.000	-3166.708	-2124.045	***
Constant	90410.963	2298.079	39.34	0.000	85906.812	94915.114	***

Mean dependent var	19256.828	SD dependent var	77418.867
Overall r-squared	0.411	Number of obs	17352.000
Chi-square	6280.929	Prob > chi2	0.000
R-squared within	0.079	R-squared between	0.410

**** p<0.01, ** p<0.05, * p<0.1*

SPATIAL ANALYSIS

Below is Figure 3, containing the results of the Spatial Lag of Xs Model. This model supports the results found with the random effects model above, as well as the labor and variable theory previously discussed. The Average Annual Wages by Industry is significant at the 1% level, with a coefficient of -1.251. This indicates that a US$ 1 raise in the annual wages of surrounding counties, on average results in 1.251 fewer employments in the subject county. This aligns with the labor and wage theory trade-off previously discussed. HHDiversity, was again not significant, although this time held a p-value of 0.125. The coefficient of HHDiversity of -44,000 suggests that higher levels of single-industry dominance in surrounding counties corresponds to 44,000 fewer employments in the subject county, however is inconclusive. Diversity of industry within a county is expected to aid overall employment levels. However, it seems that neighboring counties that are less diverse are able to absorb many more workers thank the more diverse subject county. This may be in part explained by the inherent lack of scalability of the businesses in more diverse counties, as many more of them are small or boutique firms. GDP by industry is significant on the 1% level, and indicates that neighboring counties with a dollar higher GDP correspond to 9.572 more people employed in the subject county. This concept is supported in Theory. As wage encompasses a large portion of GDP, and higher wages correspond to lower employment levels, workers from connected counties can search for and find work in the subject county resulting in 9.572 more people employed. The dummy variable HitDirect is significant on the 10% level, and indicates that if the subject county is connected to those counties which were directly hit by the hurricane the subject county has on average 2704.098 more employments. This aligns with the understanding of displaced workers finding work in the next county over, or in this case, the more connected counties. The dummy dHurricane, was not significant and therefore inconclusive. The final dummy, dNeighbor is significant on the 1% level and indicates that counties connected to "neighbor counties" (neighboring the counties directly hit by Irma) have 12,047.50 greater employment than other counties. These results support labor and disaster theory on how and whether displaced people find employment, adding rigor to the results of the Random Effects Model.

Figure 3.

Weights matrix
Name: elevenMat
Type: Imported (non-binary)
Row-standardized: No

Spatial lag model		Number of obs	= 737
		Variance ratio	= 0.996
		Squared corr.	= 0.996
Log likelihood = -8049.5323		Sigma	= 13401.02

nEmploy	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
nEmploy						
nAvgAnnualWagesb	-1.251	0.160	-7.790	0.000	-1.565	-0.936
yIndustry						
HHDiversity	-4.40e+04	28709.880	-1.530	0.125	-1.00e+05	12225.140
GDPbyIndindollars	9.572	0.082	116.910	0.000	9.411	9.732
dHitDirect	2704.098	1398.270	1.930	0.053	-36.459	5444.656
dHurr	-613.013	1216.081	-0.500	0.614	-2996.488	1770.463
dNeighbor	12047.500	1404.592	8.580	0.000	9294.554	14800.460
_cons	47871.130	6167.098	7.760	0.000	35783.840	59958.420
rho	-0.000	0.000	-28.490	0.000	-0.000	-0.000

Wald test of rho=0: chi2(1) = 811.864 (0.000)
Likelihood ratio test of rho=0: chi2(1) = 547.362 (0.000)
Lagrange multiplier test of rho=0: chi2(1) = 268.528 (0.000)

CONCLUSION

Global warming and the resulting climate change are some of the most serious and challenging problems of today. Natural disasters are more frequent and more violent than ever before, and are predicted to only worsen from here on. No matter the discipline, the study of climate change and its direct and indirect effects needs to be a primary focus for the scholarly community. This study took both a random effects approach and a spatial lag and spatial error approach to understanding how Hurricane Irma has impacted employment in Florida counties.

Through analysis of the random effects model, this study concludes that meso effects of connectivity do play an important role in a counties ability to return to pre-shock employment levels. Counties with higher degrees of connectivity resulted in higher degrees of employment. This model was inconclusive on the topic of diversity of industry. The time dummy variables, showed across the board that the hurricane had an immediate effect of diminishing employment levels, which collectively regained their pre-hurricane levels two months after the shock. The counties directly hit by the hurricane had a more pronounced drop in employment, while counties neighboring those directly hit had a diminished drop in employment. This evidence supports the theories surround neighboring employment effects.

Through analysis of the Spatial error and lag models, the results of the random effects model are supported, strengthened, and made more specific. The wage to labor theoretical neighboring relationship is supported by these models. Increases in wage in surrounding areas resulted in decreased employment in the specified area. The GDP by industry provides secondary evidence supporting the wage to labor relationship. The lag model provided evidence that counties connected to a directly hit county received a significant influx of new workers. Further, the lag model shows that counties connected to counties that physically neighbored directly hit areas received the largest share of employment. This indicates that in the event of a crisis, displacement initial happens geographically, and then in a second wave the network effects take hold. Workers then move to counties with preexisting connections.

With modern networks connecting the corners of the world together, a non-geographical approach to Spatial specification may become mainstream, as those network effects overshadow the effects of geography. This study advocates for a more widely used application of spatial economics, as it has the ability to expose nuances, otherwise hidden in the data. This study could be expanded upon by spatial evaluating all the industries. Furthermore, a side-by-side comparison with a predictive model of the pre-hurricane economic trends would be informative, as the long run difference in growth could be identified.

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