DISCUSSION PAPER SERIES

IZA DP No. 2976

How Disasters Affect Local Labor Markets: The Effects of Hurricanes in Florida

Ariel R. Belasen
Solomon W. Polachek

August 2007

Forschungsinstitut
zur Zukunft der Arbeit
Institute for the Study
of Labor

How Disasters Affect Local Labor Markets: The Effects of Hurricanes in Florida

Ariel R. Belasen
Saint Louis University

Solomon W. Polachek
State University of New York at Binghamton and IZA

Discussion Paper No. 2976
August 2007

IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

IZA Discussion Paper No. 2976
August 2007

ABSTRACT

How Disasters Affect Local Labor Markets: The Effects of Hurricanes in Florida*

Exogenous shocks often impact a local labor market more than at the national level. This study improves upon the standard Difference in Difference (DD) approach by examining exogenous shocks using a Generalized Difference in Difference (GDD) econometric approach that identifies the effects of shocks resulting from hurricanes. Based on the Quarterly Census of Employment and Wages (QCEW) data on earnings and employment, the earnings of an average worker in Florida will increase as much as four percent within the first quarter of being hit directly by a hurricane, whereas the effects of a hurricane occurring in a neighboring county move earnings per worker in the opposite direction by roughly the same percentage. As time goes by, workers in both sets of counties will experience faster growth in their earnings than workers in completely unaffected counties; however, this is coupled with a slower growth rate in employment. Powerful hurricanes have greater effects than their weaker counterparts. Additionally, the shifts in earnings and employment can be traced back, in part, to geographic features of the counties, namely that the coastal and Panhandle counties exhibit greater effects than landlocked counties. Although focus is on hurricanes in Florida, this GDD technique is applicable to a wider range of exogenous shocks.

JEL Classification: J23, J49, Q54, R11

Keywords: exogenous shock, difference-in-difference estimation, local labor markets, earnings, employment, hurricanes

Corresponding author:

Solomon W. Polachek
Department of Economics
State University of New York at Binghamton
Binghamton, New York 13902-6000
USA
E-mail: Polachek@binghamton.edu

* All data contained in this paper will be made available upon request. The authors would like to thank Joel Elvery, Christopher Hanes, Kajal Lahiri, and Stan Masters along with the seminar participants at: SUNY Albany; Binghamton University; the Third IZA Migrant Ethnicity Meeting, Washington, D.C. March 2007; and the Twelfth Society of Labor Economists Meetings, Chicago, IL May 2007 for their comments.

1. Introduction

An exogenous shock is an unexpected event that impacts a given market. Such shocks can take many forms, ranging from unexpected new legislation, to sudden population shifts, to domestic weather-related events, and even to terrorist attacks. A number of studies utilize Difference-in-Difference (DD) estimation to examine the effects of exogenous shocks. For example, Card (1990) in a well cited article used DD to examine migration and found relatively small effects on wages. Such studies look at changes across time periods between the region of interest and a comparable region which was unaffected by the shock to find long run effects. Angrist and Krueger (1999) call these results into question for failing to identify an appropriate control group. Perhaps, as a result, there is now a literature on appropriately choosing control groups, e.g. Bertrand, Duflo, and Mullainathan (2002), Kubik and Moran (2003), and Abadie, Diamond, and Hainvellen (2007).

Another problem is the experimental group. Most papers examining exogenous shocks rely on one experimental group; in Card's (1990) case, this experimental group is Miami, the site of the Mariel Boatlift. However it is not obvious that one experimental group suffices. In the Card example, the Miami labor market might not be typical of other potential experimental sites. Perhaps in his study Miami's unemployment did not rise because Miami's economy was growing more rapidly than other similarly sized cities.

One innovation of this paper is to have *many* random experimental groups as well as *many* random control sites. To achieve this, we use a different natural experiment, hurricanes, to examine the effect of an exogenous shock on a local labor market. Hurricanes, in particular, are a good choice for this study because they can affect several counties at a time, and can occur more than once in the time period under study. By having many experiment sites, we are able to test how the impact of exogenous shocks differs by both characteristics of the shock and characteristics of the experiment group. Other papers have used weather-related events (e.g. Miguel (2005), Waldman, Nicholson, and Adilov (2006), and Connolly (2007) all use rainfall) to obtain a purely exogenous variable as an instrument to predict other independent variables such as how much television children watch (in the case of Waldman, et al. (2006)), which in turn is used to predict autism using a simultaneous equation approach. We use weather (i.e. hurricanes) directly as *the* exogenous shock we want to evaluate.

To do this, we develop a Generalized Difference-in-Difference (GDD) technique in which we compare affected regions to unaffected regions across multiple exogenous events and time periods. In addition, exogenous shocks that are felt positively by one specific labor market can also have an effect on nearby labor markets. Thus we can examine multiple exogenous shocks affecting more than one locality at a time. Further, to address the issue of the appropriate definition of treatment and control group, we compare a given hurricane-stricken county to all other unaffected counties within that state. In addition, by using quarterly time-series data, this approach has the advantage of distinguishing short-term and long-term effects that previously had been neglected. In this way we can better identify the effect of an exogenous shock as well as quantify its effect over time.

The destructive power of hurricanes worldwide can wipe out thousands of lives and cause billions of dollars worth of infrastructure and private property losses annually. Hurricane season runs from June 1st through November 30th each year over warm water, i.e. oceanic temperatures exceeding 80 degrees Fahrenheit. However, the exact timing and path of the hurricanes cannot be determined in advance. Due to the high temperatures required, most hurricanes that strike the United States strike the Gulf States and the Southeastern States. Since Florida is a member of both subsets of states, it is instructive to look at the county-level Florida labor market to examine the exogenous shocks of hurricanes.

Over the course of an average year, the state of Florida will generally see one to two hurricanes during the six-month hurricane season, but there are years when Florida is not hit, even once. Over the last two years of the sample (2004 and 2005), however, the hurricanes that struck Florida were more frequent and more powerful than ever before.[1] Although hurricanes are not completely unexpected shocks to the state of Florida, each hurricane event is exogenous to the specific counties that are hit as well as to the degree of damage unleashed. Therefore, the events we have identified can be used as an independent variable by comparing those counties that have been hit to the other counties that avoided devastation.

Florida is comprised of 67 counties and, over the past 18 years, none of them have escaped the effects of hurricanes. Five of the six most damaging Atlantic Hurricanes of all time have struck Florida over the course of this time period. Damages to property can be estimated in direct monetary costs, for example, 1992's Hurricane Andrew wound up costing Southern Florida roughly $25.5 billion ($43 billion in 2005 USD) in property losses (Rappaport, 1993). But a county, business or person's wealth is made up of more than just the stock of assets owned by that person. A major portion of the flow of one's wealth comes from earned income. Thus the question is raised, how can the income-specific and employment-specific effects of a hurricane be measured? In addition, when looking at the effects of a hurricane on a specific county, are there any spillovers that need to be accounted for in neighboring counties? In addition, do more destructive hurricanes

[1] The National Oceanic and Atmospheric Association retires the names of particularly devastating hurricanes. Nine of the nineteen hurricanes in the sample occurred in the 2004 and 2005 hurricane seasons. Eight of those storms have had their names retired (as opposed to just three retirees throughout the remainder of the sample), including Hurricane Wilma which set records for intensity. Note, however, that in this past 2006 season, Florida was only hit by one minor hurricane: Ernesto, so this is not necessarily a trend moving forward.

impact labor markets more intensely? And finally, how long are the effects of a hurricane felt in earnings and employment?

The following section provides background on Florida and the hurricanes that struck the state during the time period of this study. Section three describes the economic model used to isolate and examine the effects hurricanes have had on Florida's labor market. Section four describes the econometric applications used to test the hypotheses of the model. The fifth section describes extensions to the model used to further test the hypotheses. The study concludes with a discussion of the results as well as ideas for future research.

2. Background on Florida and the Hurricanes

Over the course of the last 18 years, the state of Florida has been ravaged by 19 hurricanes. A summary Table containing descriptive statistics for each of the hurricanes can be seen in Table 1. Each hurricane is given a standard name by the World Meteorological Organization assigned to the storm in alphabetical order each year based on the timing of the storm. The lists of names for hurricanes change each year, with the gender of the initial storm also alternating each year. There are six lists in total and any time a particularly devastating hurricane occurs, the name of that hurricane is "retired" from the list (Padgett, Beven, and Free, 2004). After the sixth list is used, the first is then cycled back with any retired hurricane names replaced with new names beginning with the same letter as the retired ones.

In the late 1980s and early 1990s, there were very few hurricanes. In fact, the only hurricanes that struck Florida between 1988 and 1995 were Hurricanes Florence (September 1988) and Andrew (August 1992). While the frequency was low, the destruction was historically unparalleled. The National Oceanic Atmospheric Association (1988) reports that Hurricane

Florence caused massive flooding to the Florida panhandle, and at the time, Hurricane Andrew was the most expensive hurricane in US history (Rappaport, 1993).

In 1995, three more hurricanes struck Florida (Hurricane Allison in June, Erin in August, and Opal in September), and although none compared to Andrew in magnitude, Pasch (1996) reports that overall Allison claimed the lives of three people and Erin another six (Rappaport, 1995). Hurricane Opal, meanwhile, led to heavy casualties and cost the state of Florida three billion dollars in damages to the panhandle (Mayfield, 1998). The next five years were relatively busy yet not nearly as destructive, with Hurricanes Danny (July 1997), Earl (September 1998), Irene (October 1999), and Gordon (September 2000) all causing only minor monetary damage from flooding and rainfall (Pasch, 1997; Mayfield, 1998; Avila, 1999; and Stewart, 2001). Guiney (1999) reveals that only Hurricane Georges (September 1998) caused much damage, with 602 deaths (mainly in the Caribbean) and nearly six billion dollars in property damage to Southern Florida due to its extreme 105 miles per hour wind speeds.

Between 2001 and 2003 not a single hurricane struck Florida. But in each of the next two years, four massive hurricanes hit the state. The first of these, Hurricane Charley came in August 2004 with wind speeds reaching 150 miles per hour and led to 29 deaths and roughly $14 billion in damages to Florida (Pasch, Brown, and Blake, 2005). The next storm to hit Florida was Hurricane Frances in late August which struck at the same intensity as Hurricane Georges did six years prior. Close to three million Floridians evacuated their homes, making it the largest evacuation in Florida's history. Despite this, Beven (2004) reports that 37 Floridians died and just under $9 billion in total damage was accrued to the state due to the hurricane. The next two hurricanes were similar in magnitude to one another and hit within days of each other in the middle of September 2004. Hurricanes Ivan and Jeanne led to a combined two dozen deaths in Florida along with $20 billion worth of damages to the Southeastern United States (Stewart, 2005; Lawrence and Cobb, 2005). Ivan was particularly destructive because it hit the panhandle of Florida and crossed through several states back into the Atlantic where it recouped strength to hit Florida a second time, this time striking the southern counties.

In July of the following year, Beven (2006) reports that Hurricane Dennis killed 14 people and destroyed over two billion dollars worth of property and infrastructure in the Florida panhandle. The next storm to strike Florida, Hurricane Katrina became the most costly storm in US history with a combined $75 billion worth of damages to the Gulf States in August 2005 (Knabb, Rhome, and Brown, 2005). Hurricane Ophelia struck in September 2005 and claimed one life on the Atlantic coast of Florida (Beven and Cobb, 2006). Later that month, Hurricane Rita crossed over the Florida Keys and caused relatively light damage (Knabb, Brown, and Rhome, 2006). Many people had evacuated during Ophelia and Rita, only to find their homes unaffected by the storms, and thus decided not to evacuate for the next storm, Wilma. Unfortunately for them, Wilma, which hit in early October, set a record for being the most intense Atlantic hurricane ever. In the end, Pasch, Blake, Cobb, and Roberts (2006) report that Wilma left 35 dead and caused $12.2 billion worth of damage as it tore through the state.

Hurricanes are categorized according to the Saffir-Simpson Scale based on their wind speed. Hurricanes Florence, Allison, Erin, Danny, Earl, Irene, Gordon, Ophelia and even the Floridian part of Katrina were category one hurricanes at landfall, meaning they had wind speeds ranging between 74 and 95 miles per hour. Hurricanes Georges, Frances, and Rita were category two hurricanes and had wind speeds ranging between 96 and 110 miles per hour. With wind speeds ranging between 111 and 130 miles per hour, Hurricanes Opal, Ivan, Jeanne, and Dennis were classified as category three hurricanes. Hurricane Charley reached 150 miles per hour and became category four as it hit the mainland. Hurricanes Andrew and Wilma were category five hurricanes and had winds well above 180 miles per hour.

3. Economic Model of Hurricanes

According to Lucas and Rapping (1969), when people perceive a shock as having a temporary effect on the economy, they will not alter their long term perception of the economic variables that are affected by the shock. Hurricanes generally last for, at most, two or three days once they strike land. Historically speaking, even the damages from the most destructive hurricanes are typically repaired within two years of the hurricane. Therefore, one would expect to see perceptions of the future remain largely unchanged in the long run as the variables return to their steady state levels of growth. Guimaraes, Hefner, and Woodward (1993) state that while hurricanes create an economic disturbance in the short run, oftentimes they can lead to economic gains in the long run.

More specifically, within labor demand and labor supply, hurricanes will lead to negative shocks on labor supply in the stricken region, along with undetermined shocks to the region's labor demand as some firms attempt to fill vacancies in their workforce while others leave town with the outflow of workers. If a hurricane strikes a region and causes people to flee, the work force in that region will decrease. Therefore, labor supply would shift downward. At the same time, if that hurricane destroys a lot of private property and physical capital, labor demand could also decrease as employers have to close their shops. However, Skidmore and Toya (2002) point out that the risk of a natural disaster can reduce the expected return to physical capital (which may be destroyed during the storm) and, in turn, there is a substitution effect towards human capital as a replacement.

Of course, as the demand for human capital rises, the price of human capital will also rise. This leads to an income effect which runs counter to the substitution effect. On the other hand, if the hurricane only destroys residential areas, labor demand could also increase as employers attempt to fill vacant jobs. Thus, the shock on labor demand from a hurricane will most likely be positive leading to changes in earnings and employment.

Using the standard labor market framework, with labor supply shocked negatively and labor demand shocked positively, earnings will increase, and employment will have an ambiguous effect depending on whether or not the demand shock outweighs the supply shock. The set of earnings and employment that we are examining in this study are county-level average quarterly earnings per worker in the state of Florida. In order to measure the actual earnings effects of hurricanes on earnings, we will control for other factors that have an effect on earnings and employment. Florida's economy has been growing rapidly over the last half-century and every county in Florida has benefited from this growth. Card (1990) found that immigrants in Miami had no long-term effects on wages despite increasing the labor force by seven percent. He deduces that the Florida labor market in the 1980s was able to simply absorb a group of 45,000 immigrants into the labor market without a change in wages because of the rapid growth of Florida's economy. Ewing and Kruse (2006) isolated the specific county-level fluctuations from the overall general growth by controlling for the trend of earnings movement across the entire state. In a subsequent paper, Ewing, Kruse, and Thompson (2007) explained that local economies may be influenced by state business cycles. Following their methodology, we control for the state trends of Florida. Furthermore, Florida's labor market is greatly influenced by seasonal shifts. During the summer months, earnings and employment decrease in several sectors of the labor market. Thus, one must also control for seasonality.

In the end, we have two equations, one for employment (Q_{it}) and one for earnings (y_{it}) which sets the dependent variable equal to a function of state (Q_t, y_t), county-specific time-invariant effects (Z_i), seasonal trends (S_t) as well as hurricane effects (H_{it}):

$$Q_{it} = f(Q_t, Z_i, S_t, H_{it}) + u_{it} \tag{1}$$

$$y_{it} = f(y_t, Z_i, S_t, H_{it}) + v_{it} \tag{2}$$

As stated earlier, an important question to consider when examining hurricanes and other exogenous shocks is what kind of neighboring effects, if any, will affect the model. If a hurricane forces workers to flee one county for a second county, then labor supply in the original county will be negatively affected while labor supply in the second county will be positively affected. Thus, the model is set up to include a series of hurricane dummy variables that capture direct effects and neighboring effects. This allows us to compare three distinct sets of counties: those that were directly hit and faced heavy destruction, those that were close by, and thus affected by heavy rainfall, and those that were farther out, and generally unaffected by the hurricane. Assuming that counties i and j border one another, the subscript i under H^D indicates that the locus of destruction[2] from the hurricane is directly passing over county i while subscript ij under H^N indicates that the locus of destruction of a hurricane is passing through county j which borders county i. In other words, H^D takes a value of one when the hurricane strikes county i; and H^N takes a value of one when the hurricane strikes county j but not county i. More specifically,

[2] The locus of destruction is defined to be the area directly around the eye of the hurricane in which the radar measurements of the storm exceed 40 dBZ. For a typical hurricane, the ring's radius can measure out between 20 and 30 kilometers.

$$Q_{it} = \theta_{1i} Q_t + \theta_{2i} Z_i + \theta_{3i} Z_i t + \theta_{4i} S_t + \theta_{5i} H_{it}^D + \theta_{6i} H_{it}^N + u_{it} \tag{3}$$

$$y_{it} = \phi_{1i} y_t + \phi_{2i} Z_i + \phi_{3i} Z_i t + \phi_{4i} S_t + \phi_{5i} H_{it}^D + \phi_{6i} H_{ijt}^N + v_{it} \tag{4}$$

Since the immediate effects of hurricanes are felt in a matter of days, we will first-difference the equations to examine the changes of average quarterly earnings per worker rather than strictly looking at the levels of quarterly earnings per worker; and the changes in employment rather than the level of employment. That way we can eliminate any time-invariant county-specific effects. In addition, we also examine the change in the growth rates of employment and earnings from one period to the next, by naturally logging each equation and rewriting them in first-difference notation:

$$\Delta Q_{it} = \theta'_{1i} \Delta Q_t + \theta'_{3i} Z_i + \theta'_{4i} \Delta S_t + \theta'_{5i} \Delta H_{it}^D + \theta'_{6i} \Delta H_{ijt}^N + \Delta u_{it} \tag{5}$$

$$\Delta \ln Q_{it} = \theta_{1i} \Delta \ln Q_t + \theta_{3i} Z_i + \theta_{4i} \Delta S_t + \theta_{5i} \Delta H_{it}^D + \theta_{6i} \Delta H_{ijt}^N + \Delta u_{it} \tag{6}$$

$$\Delta y_{it} = \phi'_{1i} \Delta y_t + \phi'_{3i} Z_i + \phi'_{4i} \Delta S_t + \phi'_{5i} \Delta H_{it}^D + \phi'_{6i} \Delta H_{ijt}^N + \Delta v_{it} \tag{7}$$

$$\Delta \ln y_{it} = \phi_{1i} \Delta \ln y_t + \phi_{3i} Z_i + \phi_{4i} \Delta S_t + \phi_{5i} \Delta H_{it}^D + \phi_{6i} \Delta H_{ijt}^N + \Delta v_{it} \tag{8}$$

Due to space limitations, we only present the results relating to equations (6) and (8). Results for the other equations are available upon request.

4. Application of the Model

Theoretically, employment in the average Florida county should increase by the same percentage as employment in Florida as a whole increases. With such uniform growth, the coefficient for state employment (θ_{1i}) should be positive and equal to one when Q_t is defined as average county employment. Thus we measure Q_t as state employment in time t divided by 67 (the number of Florida counties). Similarly, uniform growth implies ϕ_{1i} in (8) should be one when y_t is defined as earnings per worker. The summer seasonal trend appears to strictly impact the labor supply function by increasing employment and thus decreasing earnings, so we expect to see $\theta_{4i} > 0$ and $\phi_{4i} < 0$. Economic theory predicting that labor supply and labor demand offset each other with regards to employment, and/or that labor demand is highly inelastic implies that $\theta_{5i} < 0$ and $\theta_{6i} > 0$. Finally, since hurricanes negatively affect labor supply in the county that gets hit and positively affect labor supply in nearby counties as workers relocate, ϕ_{5i} should be positive and ϕ_{6i} should be negative as the equilibrium wage adjusts to the change in employment. And because workers from the same stricken county may flee to several different counties, the magnitude of ϕ_{5i} should be greater than that of ϕ_{6i} because the impact on a directly hit county will likely be greater than on a county that was nearby a hurricane.

The hurricane data used in this analysis come from the National Hurricane Center of the National Oceanic and Atmospheric Association (NOAA).[3] The NOAA is a federal agency within the Department of Commerce that examines the conditions of the oceans and the atmosphere. In particular, the NOAA evaluates ecosystems, climatic changes, weather and water cycles, and commerce and transportation. The Pew Center on Global Climate Change (2006) reports that the strength and frequency of hurricanes have increased to unprecedented levels over the past decade. In the last few years specifically we have seen hurricanes appear in places like the South Atlantic that had previously been thought of as safe from hurricanes. One such storm struck Brazil in March

[3] National Oceanic and Atmospheric Association, http://www.noaa.gov/

2004 and wreaked havoc along the coastline because people had not had any experience dealing with hurricanes (Climate.org, 2004). Even Florida, with its high rate of storms each year, has had difficulty dealing with the higher frequency and higher magnitude storms in the past few years. Therefore, to balance the high intensity of the last decade we are also including hurricanes that struck Florida in the decade prior to this one. All in all, 19 hurricanes of varying strength struck Florida in the 18 year period between 1988 and 2005.

To coincide with this time period, quarterly employment[4] and average quarterly earnings data from the Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages (QCEW)[5] were used, spanning the time period starting with the first quarter of 1988 and continuing through the fourth quarter of 2005.[6] The BLS surveys employers regarding their total wage bill and employment each quarter. The employers are sorted by county, such that each report of employment is recorded for the county in which the workers are employed.

The regression can be run using a GDD procedure which is similar to a DD approach taken over multiple events and time periods to compare the effects of hurricanes on Florida's counties. The process estimates the difference between the first differenced fixed-effects transformation to calculate the impact of hurricanes by comparing the counties that were hit to those counties that were not hit. Thus, we force the coefficient on the state trend to be equal to one by bringing $\Delta \ln Q_t$ and $\Delta \ln y_t$ to the left-hand side of the regression, and then re-label the coefficients sequentially for ease of comparison:

[4] Some employment data were available in a monthly format as well, and whenever possible, monthly data were used for employment.
[5] Bureau of Labor Statistics, http://www.bls.gov/
[6] Hourly employment data would be preferable for this study, however, due to data limitations, total employment numbers were used instead.

$$(\Delta \ln Q_{it} - \Delta \ln Q_t) = \alpha_1 Z_i + \alpha_2 \Delta S_t + \alpha_3 \Delta H_{it}^D + \alpha_4 \Delta H_{ijt}^N \qquad (9)$$

$$(\Delta \ln y_{it} - \Delta \ln y_t) = \delta_1 Z_i + \delta_2 \Delta S_t + \delta_3 \Delta H_{it}^D + \delta_4 \Delta H_{ijt}^N \qquad (10)$$

The dependent variables now measure the degree a county's per worker wage and a country's employment deviate from the average Florida county.

As mentioned before, a value of one for ΔH_{it}^D implies that a hurricane passed right through county *i* at time *t*. A value of one for ΔH_{ijt}^N implies that a hurricane did not strike county *i*, but instead struck a county that neighbors county *i*. In that way, any indirect neighboring effect from a hurricane will be captured in the data. We used the detailed magnitudes and coordinates from the NOAA to trace the path of destruction that the hurricanes left behind as they passed through Florida.[7] At this point we assume that all time-invariant county-specific effects will have no effect on growth, and thus the Z_i terms will take values of zero. This assumption is relaxed in the next section where we explore geographic differences. The results are captured in the first model of Tables 2 and 3.

The coefficients that are of interest to this study are α_3, α_4, δ_3, and δ_4, which respectively, are the direct and neighboring effects coefficients of hurricanes for each of the four equations. In employment equation (9), α_3 should reflect the average percent deviation in employment growth between a county hit by a hurricane and one not hit. Likewise, α_4 should represent the average percent deviation in employment growth between a county bordering a county hit by a hurricane and an average Florida county. We see that the number of workers falls by an average of 2.37% in

[7] To trace the path, we used Google Earth (2006) software package available for download at http://earth.google.com/.

counties that are struck directly by hurricanes relative to other counties (see Model 1 in Table 2).[8] The effect on neighboring counties is statistically insignificant, thus they do not incur a noticeable change in the size of their employment.

The coefficients for the earnings function, equation (10), can be interpreted as the average change in the growth rate of earnings per worker relative to the typical county. One can see from the results in Table 3 that the growth rate of earnings will change significantly in each of these two county types, with the directly hit counties' growth rates of earnings increasing by 1.92% on average in the quarter that the hurricane hits county *i* (see Model 1 in Table 3). Similarly, the estimate for δ_4 indicates that the growth rate of earnings will fall by 0.93% on average in the quarter in which a hurricane strikes a county that is neighboring county *i*.

The underlying intuition behind these changes is that in directly hit counties labor supply will shift inwards after a hurricane, thus leading to a decrease in employment and a subsequent increase in earnings. Within the neighboring counties where residents will experience lighter flood damage, it appears that earnings fall despite no overall increase in employment. Belasen and Polachek (2007) show that this pattern is due to a change in the sectoral structure of the labor market in these counties. High wage earners that are able to flee to safer regions will do so, leaving the low wage earners in their wake. Finally, as expected, the seasonal variables in the employment equation are significantly positive for the change in employment and negative for the employment equations which accounts for the summer trend in the state of Florida.

A significant source of error in this study lies with workers who do not work in the county they reside in. While most workers prefer to work near their homes, there will be a significant portion of the workforce that travels a long distance to and from work each day. Additionally, if a

[8] This value is computed by comparing the additional change in employment incurred by the average hurricane-stricken county relative to the average unaffected county across the quarter in which a hurricane hit

county is declared a disaster zone, oftentimes relief workers are brought in from out of state and are not considered to be employed in the county they are assisting. We assume that these outliers are evenly distributed across the state labor market and thus should not affect any single county more than any other.[9]

5. Extensions of the Model

5.1. Intensity Effects

Noting that the direct effects of hurricanes lead to increases in earnings, while neighboring effects lead to decreases in earnings, the question can be raised: Are the earnings effects similar across all hurricanes individually or are they more pronounced when a combination strike a county within the same time period? Equations (11) and (12) add in a dummy variable (*M*) to represent the presence of multiple hurricanes. Multiple hurricane events are separated from individual hurricanes by including an interaction term between the hurricane effect and the *M* dummy:

$$(\Delta \ln Q_{it} - \Delta \ln Q_t) = \alpha_1 \Delta S_t + \alpha_2 \Delta H_{it}^D + \alpha_3 \Delta H_{ijt}^N + \alpha_4 M + \alpha_5 (\Delta H_{it}^D * M) + \alpha_6 (\Delta H_{ijt}^N * M) \quad (11)$$

$$(\Delta \ln y_{it} - \Delta \ln y_t) = \delta_1 \Delta S_t + \delta_2 \Delta H_{it}^D + \delta_3 \Delta H_{ijt}^N + \delta_4 M + \delta_5 (\Delta H_{it}^D * M) + \delta_6 (\Delta H_{ijt}^N * M) \quad (12)$$

[9] According to Joel Elvery of the BLS, the QCEW attempts to get accurate data on the relief workers via the source of their employment.

M, is interacted with ΔH^D and ΔH^N so that when a multitude of hurricanes strike a county in Florida, M will take a value equal to one. The derivative of the difference in employment growth with respect to ΔH^D will equal ($\alpha_2 + \alpha_5$), and it will equal ($\alpha_3 + \alpha_6$) when taken with respect to ΔH^N. The derivative of the difference in earnings growth with respect to ΔH^D will equal ($\delta_2 + \delta_5$), and it will equal ($\delta_3 + \delta_6$) when taken with respect to ΔH^N. The interpretation of each of these derivatives is the difference in the growth rate of employment (or earnings) between the average hurricane afflicted county and the overall average county. More specifically, α_5 and δ_5 reflect the additional effect on employment and earnings resulting when multiple hurricanes strike a single county within the same quarter. One would suspect that a multitude of hurricanes will be much more destructive than a single hurricane and thus lead to much more capital loss and potential dispersion of the labor force, and therefore should have greater affects on labor demand and labor supply. The results of the regression can be found in Tables 2 and 3 under Model 2.[10]

The coefficient for the interaction term of M with the direct effect in the employment equation reveals no additional effect on employment growth resulting from multiple hurricanes beyond the effect of the initial hurricane. On the other hand, we find a significant effect for earnings. When multiple hurricanes directly strike a county, the relative growth rate of earnings in that county will rise by 2.5% on average. Note, however, that this increase replaces the standard direct effect which is now insignificant.[11] Neighboring counties do not face any additional effects resulting from a multitude of hurricanes.

[10] To conserve space, we do not report α_4 and δ_4, or other "stand alone" dummy variables that correspond to other interaction models described later in the text.

[11] Models 3, 4, and 5 in Tables 2 and 3 employ alternative measures of hurricane intensity using a similar format as the multiple hurricane equations. Model 3 examines the impact of hurricane death tolls; Model 4 differentiates between hurricanes whose names have been retired from other hurricanes; and Model 5 examines the monetary damage (in billions of 2005 dollars) to the State of Florida from each hurricane. (While county-level data would be more desirable, data limitations forced us to use state-level damage data.) In each instance, the effects were minor, if at all significant.

Additionally, we also split up the hurricanes into two subcategories based on the Saffir-Simpson Scale. Hurricanes which fell into categories 1, 2, or 3 made up the low intensity group (SS1), and hurricanes in categories 4 or 5 were placed into the high intensity group (SS2). The group variables now replace the hurricane variables from the initial model. Thus the model takes the following form, where $SS1$ and $SS2$ correspond to the two Saffir-Simpson groups:

$$(\Delta \ln Q_{it} - \Delta \ln Q_t) = \alpha_1 \Delta S_t + \alpha_{21} \Delta SS1_{it}^D + \alpha_{22} SS2_{it}^D + \alpha_{31} \Delta SS1_{ijt}^N + \alpha_{32} \Delta SS2_{ijt}^N \tag{13}$$

$$(\Delta \ln y_{it} - \Delta \ln y_t) = \delta_1 \Delta S_t + \delta_{21} \Delta SS1_{it}^D + \delta_{22} \Delta SS2_{it}^D + \delta_{31} \Delta SS1_{ijt}^N + \delta_{32} \Delta SS2_{ijt}^N \tag{14}$$

Table 4 outlines the results of these regressions. High intensity hurricanes have a much greater impact on earnings than we have seen in previous models, as they boost the growth rate of earnings per worker by 4.35% on average relative to workers in the average county. There is also a greater magnitude effect on employment, as it drops by 4.76% on average relative to the average county. Meanwhile, counties that neighbor the directly hit county will not face an effect on employment from the high intensity hurricanes, but will experience a 3.33% decline in wage growth relative to the typical county. Low intensity hurricanes, on the other hand, will relatively decrease employment by just 1.47% and boost earnings growth by 1.28% on average in directly hit counties. In neighboring counties, they will decrease to the average earnings growth rate by 4.51%. As such, it appears that more severe storms have a greater impact on the labor market.

5.2. Timing Effects

Another extension that can be made is to examine the impact of hurricanes over time. Equations (9) and (10) can be augmented using a series of hurricane dummy variables that capture the effects of hurricanes over time to see if there is any lasting impact. The vector $\vec{H}^D = (H_{it}^D, H_{it-1}^D, H_{it-2}^D, \ldots)$ is used to represent the series of direct effects and $\vec{H}^N = (H_{ijt}^N, H_{ijt-1}^N, H_{ijt-2}^N, \ldots)$ to reflect the neighboring effects. Subscript *i* indicates that the hurricane is directly affecting county *i*, the lag indicates how far back in time the hurricane hit, and subscript *ij* indicates that a hurricane from county *j* affects county *i*. The coefficients for each of these vectors are vectors themselves, and thus the model now takes the form:

$$(\Delta \ln Q_{it} - \Delta \ln Q_t) = \alpha_{1i} \Delta S_t + \Delta \vec{H}_{it}^D \vec{\alpha}_{ki} + \Delta \vec{H}_{ijt}^N \vec{\alpha}_{li} \quad (15)$$

$$(\Delta \ln y_{it} - \Delta \ln y_t) = \delta_{1i} \Delta S_t + \Delta \vec{H}_{it}^D \vec{\delta}_{ki} + \Delta \vec{H}_{ijt}^N \vec{\delta}_{li} \quad (16)$$

As mentioned, according to Lucas and Rapping (1969), one can expect the steady state growth level of earnings to be unaffected by a hurricane event in the long run, but for there to be temporary adjustments in the short run. Guimaraes et al. (1993) found different signs for the initial impact of the hurricanes and for their long-run effects in which Hurricane Hugo impacted South Carolina's economy. The lagged effects lasted for eight quarters following the hurricane. Furthermore, Ewing et al. (2007) (which only deals with the Oklahoma City tornado) and Ewing and Kruse (2006) (which focuses primarily on Hurricane Bertha) each found that earnings will jump immediately and then converge back towards pre-hurricane levels; and while hurricanes create an economic disturbance in the short run, oftentimes they can lead to economic gains in the long run.

Therefore, the coefficients for the time delayed direct effects should, for the most part, be negative for earnings growth as the values come back down towards their steady state from the hurricane-induced increases, however, we expect the cumulative effect to yield a slightly positive upswing in earnings to match the findings from earlier papers. Employment, on the other hand, should increase over time as workers return to the rebuilt economy. The neighboring effects occur primarily because labor supply rises as a spillover effect as workers flee hurricane-stricken counties. The influx of workers looking for refuge will lead to a decline in earnings in that county; so one would expect to see earnings rise slightly as some workers relocate back out of county *i*, but the steady state growth level could still wind up lower than its initial point since many displaced people may never return to their original county.

Figures 1 and 2 (below) show the results of the regressions containing the direct and the neighboring effects of a hurricane in time *t* as well as the lingering effects of that hurricane for eight quarters (or 24 months) following the storm.[12] What the results imply is that, similar to the time of the hurricane strike, the lagged effects on employment are also likely mitigated by opposing labor market shifts across industries.

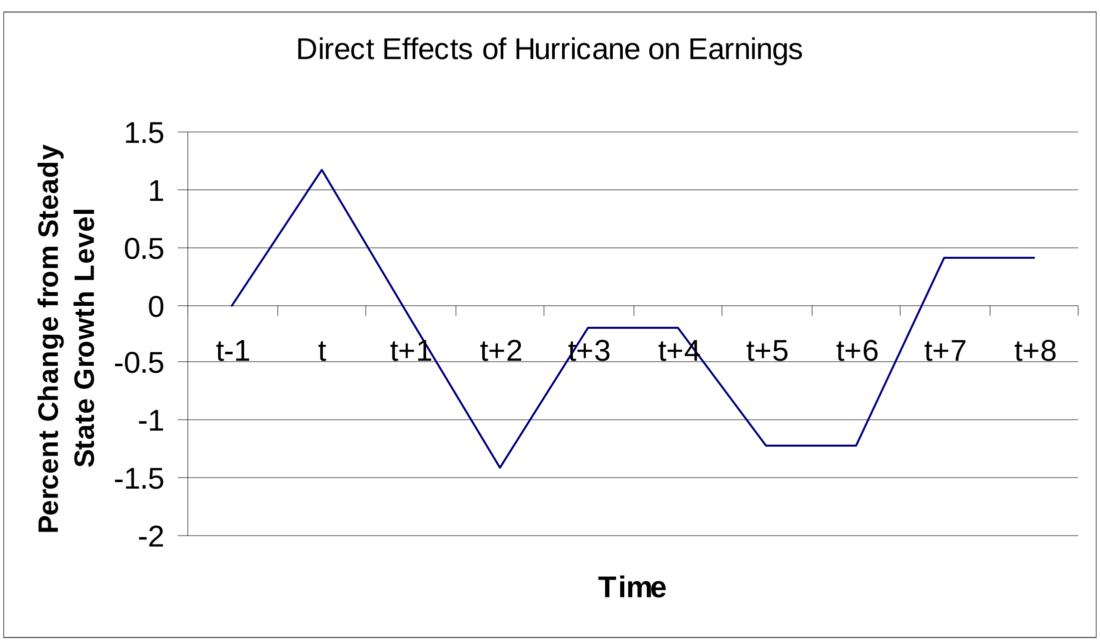

Figure 1: Average Direct Effects of a Hurricane on Earnings over a Two-Year Duration

[12] A table of the regression results is available upon request.

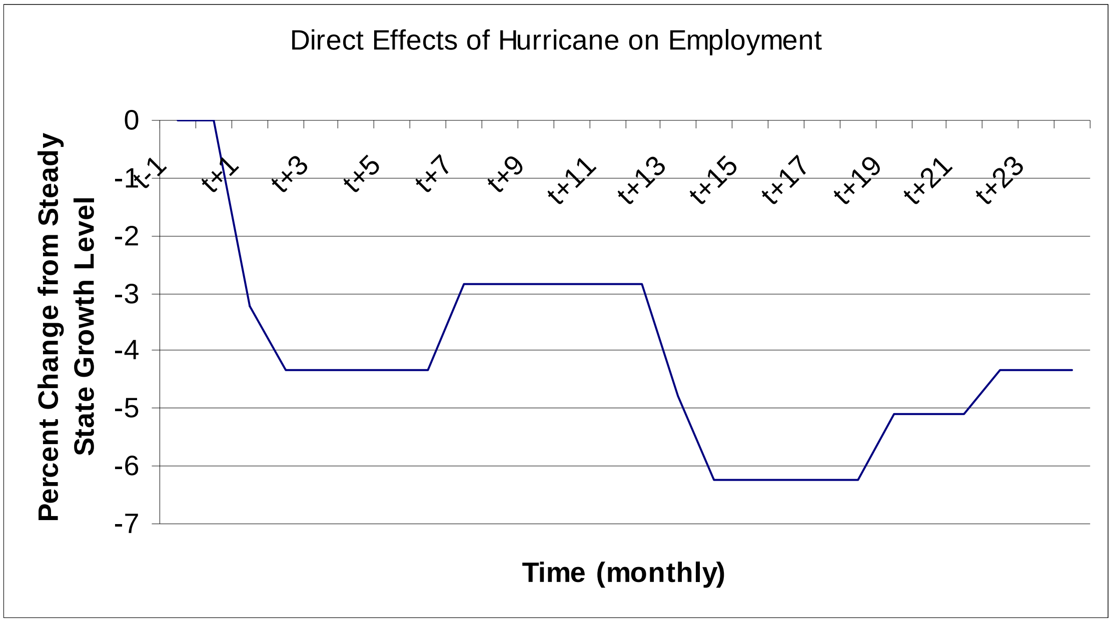

Figure 2: Average Direct Effects of a Hurricane on Employment over a Two-Year Duration

The direct effects of an average hurricane are pronounced on earnings growth up through the seventh quarter following the time of the disaster. For neighboring counties, on the other hand, the effects on earnings growth, on average, last into the eighth quarter.[13] Unlike the Guimaraes et al. (1993) study of Hugo, however, not all of the lags significantly impact earnings and employment growth. The disparity can be explained by Ewing and Kruse's (2006) finding that the effect of a given hurricane is mitigated by the occurrence of other hurricanes within the same time period. If the time delayed effects of one storm coincide with the immediate impact of a second storm, then the effects of both might be difficult to identify and as a result they may be understated in the model.

[13] Ninth and tenth lags were performed as well to verify these findings, and both came up insignificant for each regression.

What can be seen in Figure 1 is that a hurricane will immediately boost growth in earnings in the counties where it strikes followed by an immediate downturn one quarter later. As time goes by, earnings growth will continue to follow this pattern before settling in at a new steady state level roughly 0.40% above the level of growth for an average county. While this in no way indicates that earnings growth in a hurricane stricken county will permanently remain higher than in a county that has avoided the hurricane, it does imply that the temporary wage gains may not be as short term as the ones Guimaraes et al. (1993) reported based on Hurricane Hugo. On the other hand, these findings are consistent with the existing literature of Ewing et al. (2007) and Ewing and Kruse (2006) which found that after a hurricane, earnings will jump immediately and then converge back towards pre-hurricane levels. Additionally, they find that while hurricanes create an economic disturbance in the short run, oftentimes they can lead to economic gains in the long run, just as we have found in this paper.

Figure 2 illustrates the cumulative monthly growth rate of employment. We find that the labor market takes a cobweb form in which employment jumps about a year after the hurricane (coinciding with a decrease in earnings) and then decreases as earnings increase before settling at a growth rate 4.32% lower than that of unaffected counties.

The effects of hurricanes on neighboring counties have similar results, but take a different course. If a hurricane strikes a county neighboring county *i*, earnings growth will immediately fall in county *i* until they are roughly 1.62% lower on average than the earnings growth level of a worker in a typical county. It appears as though neighboring counties go through similar earnings changes around the third quarter following the hurricane as do directly hit counties, as wage growth rises above the original level and continues to cycle up and down until two years after the storm to wind up 1.06% below the earnings growth level in an average county. Additionally, as with the directly hit counties, employment in neighboring counties mirrors earnings in those counties. It too appears to take a cobweb format, where an increase in earnings corresponds with a decrease in employment, and vice versa. Employment growth increases from the initial level; and after cycling along with earnings, employment growth ends up 0.49% above that of an average unaffected county. (see Figures 3 and 4 below):

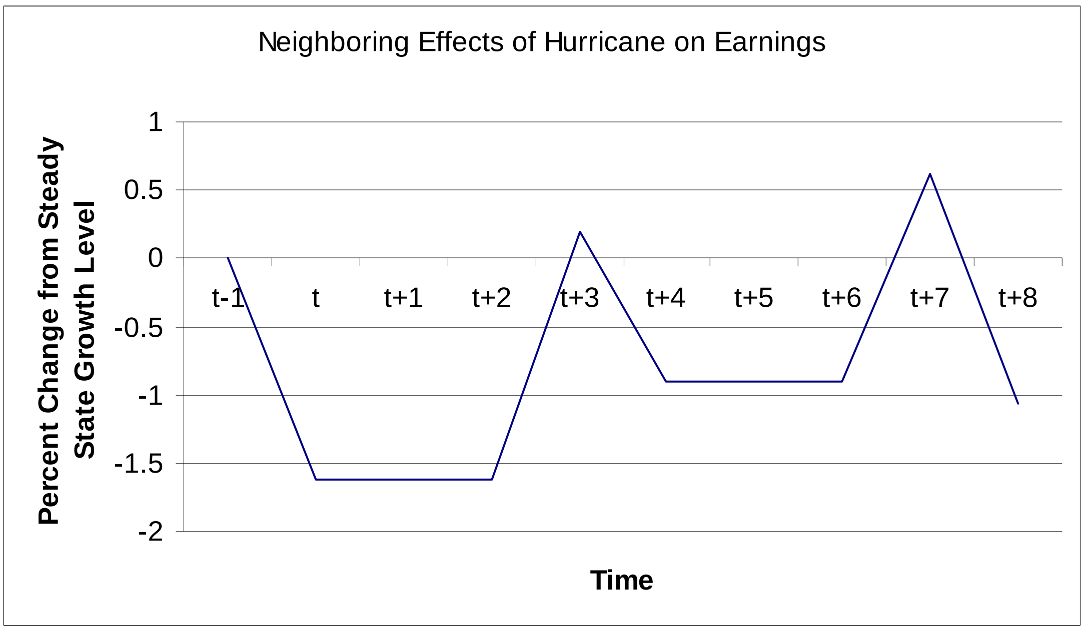

Figure 3: Average Neighboring Effects of a Hurricane on Earnings over a two-year Duration

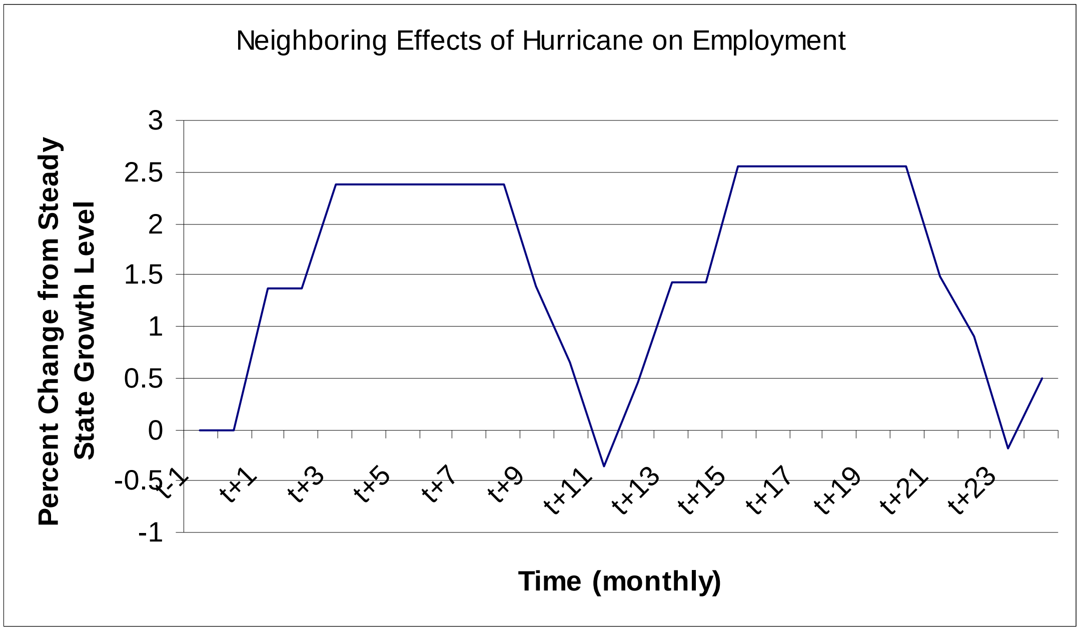

Figure 4: Average Neighboring Effects of Hurricane on Employment over a 2-year Duration

At certain points in time, earnings growth will be higher in hurricane-impacted counties than in other counties while employment growth will remain relatively unchanged. This is likely a result of low wage earners being replaced by high wage earners in the specified counties. Card (1990) and Belasen and Polachek (2007) each have results that are consistent with these findings.[14]

5.3. Geographic Effects

Thus far, we have studied the effects of hurricanes on three separate groups of counties in Florida: those that were directly hit by the storm, those neighboring the counties that were directly hit, and all other counties. Theoretically speaking we expect that the neighboring effect should diminish with distance, so a town located 100 miles away from a directly hit county should face a

[14] Other time-related applications that can be drawn from this particular regression are to see if specific time-related events (such as elections or the September 11 terror attack) had any impact on the hurricane effects. As with the additional specifications for intensity effects, these additional time-related effects were also insignificant. However, it appears that timing within a quarter can alter the impact of a hurricane on the labor market, such that hurricanes that occur early on in the quarter will have less of an effect than other hurricanes. This is likely due to the fact that hurricanes last for a week at most and are typically dealt with soon after (see models 6 and 7 in tables 2 and 3).

stronger neighboring effect than a town located 200 miles away since the flooding will be greater as the proximity to the locus of destruction increases. To verify this expectation, we fit equations (9) and (10) with a "Second County Away" variable to capture the effects of hurricanes on the counties which lay two away from the directly hit counties:

$$(\Delta \ln Q_{it} - \Delta \ln Q_t) = \alpha_1 \Delta S_t + \alpha_2 \Delta H_{it}^{D} + \alpha_3 \Delta H_{ijt}^{N} + \alpha_4 \Delta H_{ikt}^{2} \tag{17}$$

$$(\Delta \ln y_{it} - \Delta \ln y_t) = \delta_1 \Delta S_t + \delta_2 \Delta H_{it}^{D} + \delta_3 \Delta H_{ijt}^{N} + \delta_4 \Delta H_{ikt}^{2} \tag{18}$$

The new variable ΔH_{ikt}^{2} takes a value of one for county *i* when a hurricane strikes county *k* if that county *k* is two counties away from county *i*. In other words, it is essentially the neighboring effect of the original neighboring effect. One would, therefore, expect to see the coefficients for the neighboring effect and the second-county-away effect to take the same sign, but for the second-county-away coefficient to be smaller in magnitude (or insignificant as the case may be). Model 8 in Tables 2 and 3 report the results of these regressions.

Similar to the neighboring effect, the two-away effect is insignificant for employment. In fact, the neighboring effect and the second-county-away effect on average earnings are nearly identical in sign and magnitude. However, the second-county-away effect is less significant, thus one can argue that it holds up to the theoretical expectations. In addition, we find that the second-county-away effect is insignificant which also verifies expectations. In sum, we are able to conclude from this that the neighboring effect of hurricanes found in earnings diminishes with distance from the path of the storm.

A final extension incorporates geographic location into the model to examine whether certain areas of Florida are affected more heavily by hurricanes than others. To that end, we differentiate between coastal and landlocked counties, as well as between counties located on the panhandle or in the rest of the state. Coastal counties experience more flooding than landlocked counties and generally find themselves facing higher monetary costs for rebuilding. The hurricane effects, therefore, should be more pronounced for coastal counties. Panhandle counties draw most of their economic growth from tourism whereas other counties tend to have a better developed industrial infrastructure. Therefore we expect to see weaker increases in earnings for directly hit panhandle counties and stronger decreases for neighboring panhandle counties since tourism revenues are likely to diminish all across the panhandle after a hurricane strikes there. Equations (9) and (10) are fit with a variable C to distinguish coastal counties from non-coastal counties and a variable P to distinguish between those counties lying on the panhandle versus all other counties. Furthermore, a great deal of panhandle counties lie on the coast so there is an interaction between the two sets of geographic comparisons. To that end, we also separate out those counties that meet both qualifications by adding in a series of interaction terms for both C and P:

$$\begin{aligned}(\Delta \ln Q_{it} - \Delta \ln Q_t) &= \alpha_1 \Delta S_t + \alpha_2 \Delta H_{it}^D + \alpha_3 \Delta H_{ijt}^N \\ &+ \alpha_4 C + \alpha_5 P + \alpha_6 (C * P) + \alpha_7 (\Delta H_{it}^D * C) + \alpha_8 (\Delta H_{ijt}^N * C) \\ &+ \alpha_9 (\Delta H_{it}^D * P) + \alpha_{10} (\Delta H_{ijt}^N * P) + \alpha_{11} (\Delta H_{it}^D * C * P) + \alpha_{12} (\Delta H_{ijt}^N * C * P) \end{aligned} \tag{19}$$

$$\begin{aligned}(\Delta \ln y_{it} - \Delta \ln y_t) &= \delta_1 \Delta S_t + \delta_2 \Delta H_{it}^D + \delta_3 \Delta H_{ijt}^N \\ &+ \delta_4 C + \delta_5 P + \delta_6 (C * P) + \delta_7 (\Delta H_{it}^D * C) + \delta_8 (\Delta H_{ijt}^N * C) \\ &+ \delta_9 (\Delta H_{it}^D * P) + \delta_{10} (\Delta H_{ijt}^N * P) + \delta_{11} (\Delta H_{it}^D * C * P) + \delta_{12} (\Delta H_{ijt}^N * C * P) \end{aligned} \tag{20}$$

Models 9, 10, and 11 in Tables 2 and 3 each fit the original model with the coastal and/or panhandle variables (independently as well as together) and their interactions with the hurricanes. Coastal counties and panhandle counties tend to have a lower change in employment than the rest of the state. However, the impact of hurricanes on employment does not appear to be any different across the different geographic classifications. Both coastal and panhandle counties also exhibit a greater increase in earnings than the rest of the state. And while there is no discernable difference between the different types of counties after a direct hit from a hurricane, neighboring effects change drastically by isolating the geographic characteristics of the county.

Explicitly accounting for the panhandle in Models 10 and 11 appears to somewhat negate the overall effects of hurricanes on the average neighboring county. Whereas the ΔH_{ijt}^{N} coefficient becomes insignificant, the interaction term between the panhandle and the neighboring hurricane variables is significantly negative. This implies that neighbors of panhandle counties are the counties most affected by hurricanes. Relative earnings in these counties fall 3.21 to 5.31% when their neighbors in the panhandle are hit by a hurricane. Neighbors of coastal states hit by a hurricane are negligibly affected as earnings fall only by -0.01% (Models 9 and 11). Finally, the magnitude of employment effects is much greater for both direct and neighboring counties relative to the typical county if those hurricane-impacted counties lie both along the coast and the Panhandle.

6. Conclusion

As illustrated by hurricanes, exogenous shocks to an economy will lead to opposing shifts in wages and the size of the labor force across neighboring local labor markets. Therefore exogenous factors that may not appear to have much of an impact on a macro scale, may yet play a major role in shaping the differences across local markets.

The devastation and frequency of hurricanes in the North Atlantic Ocean is unparalleled relative to other natural disasters in the United States. The widespread devastation of hurricanes can wipe out infrastructure, private homes, businesses, and even entire communities. While the effects can be measured by looking directly at the loss of life and damage to property, there are also indirect results of a hurricane. One such result is the effect of hurricanes on local labor markets. This paper developed a GDD model that, through various specifications, isolated two distinct effects hurricanes have on labor markets. The first involves the specific counties directly struck by hurricanes. Here the hurricane decreases employment in the stricken counties while at the same time boosting earnings, thus appearing to negatively impact labor supply, while at the same time changing the labor demand for certain industrial sectors. And as workers flee the devastation by heading into neighboring counties, those counties experience a positive labor supply shock moving the equilibrium downward along what appears to be a perfectly inelastic labor demand curve. The result is that employment is relatively unchanged, while earnings will have decreased.

We find that as a portion of the labor force flees a hurricane-stricken county, the growth of earnings per worker remaining in that county of Florida will increase up to 4.35% relative to workers outside that county. Meanwhile, as workers flow into nearby counties, the growth of earnings per worker in those regions will decrease by as much as 4.51%. Even two years after the hurricane, earnings may still remain higher in areas hit by a hurricane than elsewhere.

Particularly in today's age of increased intensity, duration, and sheer quantity of tropical storms, policymakers looking to rebuild hurricane damaged economies can point to the wage benefits for workers who relocate to regions that have been hit by hurricanes. This entails both short-term and long-term effects on both directly hit and neighboring counties, which we find to exhibit somewhat of a cobweb quarter-by-quarter. These findings should help policy makers assess such issues as UI eligibility. In addition, it should help policy makers in areas outside of the Southeast US such as California, Mexico, and Brazil that are now being hit by hurricanes due to recent weather changes.

Subsequent studies related to Generalized Difference-in-Difference could include the examination of the impact of unplanned illegal immigration on local economies or the influx of a new disease. In addition, the exogenous effects of other natural disasters (i.e. earthquakes, tornados, tsunamis, etc.) could also be captured by this model using the same framework. In addition, other variables of study could include FEMA funding and other economic specifications (such as GDP growth, consumer spending, industrial growth, etc.).

Table 1: Descriptive Statistics

Hurricane	Synoptic Lifecycle	Damage to Florida	Deaths in FL	Windspeed at Landfall	Average Rainfall	Saffir Simpson Scale
Florence	September 1988	$0.6 million	0	75 mph	5"-10"	1
Andrew	August 1992	$43 billion	44	175 mph	5"-7"	5
Allison	June 1995	$1.2 million	0	75 mph	4"-6"	1
Erin	August 1995	$0.5 million	6	87 mph	5"-12"	1
Opal	September 1995	$4.4 billion	1	115 mph	5"-10"	3
Danny	July 1997	$100 million total to US	0	80 mph	2"-7"	1
Earl	September 1998	$64.5 million	2	92 mph	6"-16"	1
Georges	September 1998	$392 million	0	103 mph	8"-25"	2
Irene	October 1999	$1.1 billion	8	75 mph	10"-20"	1
Gordon	September 2000	$11.9 million	1	75 mph	3"-5"	1
Charley	August 2004	$15.1 billion	29	150 mph	5"-8"	4
Frances	September 2004	$8.9 billion	37	105 mph	10"-20"	2
Ivan	September 2004	$8.1 billion	19	130 mph	7"-15"	3
Jeanne	September 2004	$6.9 billion total to US	3	121 mph	8"-13"	3
Dennis	July 2005	$2.2 billion	14	120 mph	10"-15"	3
Katrina	August 2005	$115 billion total to US	14	81 mph	5"-15"	1
Ophelia	September 2005	$70 million total to US	1	80 mph	3"-5"	1
Rita	September 2005	$10 billion total to US	2	80 mph	2"-4"	1
Wilma	October 2005	$12.2 billion	35	120 mph	7"-12"	3

Notes: Data compiled from NOAA reports; Retired Hurricanes are *italicized*; all damage is to Florida unless otherwise noted.

Table 2: GDD Regression Results on Change in Growth of Employment in a Hurricane-Stricken County Relative to an Average County

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
Summer Seasonal Effect											
Coefficient:	0.0163***	0.0152***	0.0162***	0.0165***	0.0162***	0.0164***	0.0166***	0.0163***	0.0163***	0.0164***	0.0163***
P-value:	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Direct Effect of Hurricanes											
Coefficient:	-0.0237***	-0.0149**	-0.0132**	-0.0115	-0.0129**	-0.0242***	-0.0301***	-0.0235***	-0.0440***	-0.0316***	-0.0702***
P-value:	*0.000*	*0.019*	*0.047*	*0.121*	*0.038*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*
Neighboring Effect of Hurricanes											
Coefficient:	0.0024	0.0175**	0.0042	0.0013	0.0034	0.0017	-0.0001	0.0036	0.0015	0.0002	0.0171*
P-value:	*0.594*	*0.045*	*0.482*	*0.844*	*0.528*	*0.721*	*0.990*	*0.429*	*0.832*	*0.979*	*0.096*
Interaction of Direct and Multiple											
Coefficient:		-0.0133									
P-value:		*0.203*									
Interaction of Neighboring and Multiple											
Coefficient		-0.0022									
P-value:		*0.838*									
Interaction of Direct and Death Toll											
Coefficient:			-0.0004								
P-value:			*0.227*								
Interaction of Neighboring and Death Toll											
Coefficient:			0.0003								
P-value:			*0.396*								
Interaction of Direct and Retired											
Coefficient:				-0.0111							
P-value:				*0.411*							
Interaction of Neighboring and Retired											
Coefficient:				0.0217							
P-value:				*0.116*							
Interaction of Direct and Damage											
Coefficient:					-0.0011						
P-value:					*0.104*						
Interaction of Neighboring and Damage											
Coefficient:					0.0004						
P-value:					*0.525*						
Interaction of Direct and Election											
Coefficient:						0.0046					
P-value:						*0.798*					
Interaction of Neighboring and Election											
Coefficient:						0.0054					
P-value:						*0.708*					
Interaction of Direct and Early											
Coefficient:							0.0308***				
P-value:							*0.005*				
Interaction of Neighboring and Early											
Coefficient:							0.0320***				
P-value:							*0.010*				
Second County Away Effect											
Coefficient:								-0.0081			
P-value:								*0.152*			
Interaction of Direct and Coastal											
Coefficient:									0.0348***		0.0636***
P-value:									*0.001*		*0.000*
Interaction of Neighboring and Coastal											
Coefficient:									0.0019		-0.0222*
P-value:									*0.835*		*0.077*
Interaction of Direct and Panhandle											
Coefficient:										0.0265**	0.0749***
P-value:										*0.012*	*0.000*
Interaction of Neighboring and Panhandle											
Coefficient:										0.0069	-0.0223
P-value:										*0.442*	*0.129*
Interaction of Direct and C-P											
Coefficient:											-0.0813***
P-value:											*0.000*
Interaction of Neighboring and C-P											
Coefficient:											0.0433**
P-value:											*0.019*
R^2	**0.0221**	**0.0268**	**0.0233**	**0.0237**	**0.0238**	**0.0222**	**0.0260**	**0.0226**	**0.0249**	**0.0238**	**0.0299**
F	**35.35**	**21.46**	**18.62**	**18.95**	**19.05**	**17.74**	**20.88**	**27.03**	**23.97**	**22.84**	**16.04**
n, groups	4757, 67	4757, 67	4757, 67	4757, 67	4757, 67	4757, 67	4757, 67	4757, 67	4757, 67	4757, 67	4757, 67

Note: Table reports selected coefficients of equations (9, 11, 15, 17, and 19) fit with QCEW data. See text for details. Included but not reported variables are the stand-alone dummy variables for each equation that correspond to each interaction term. *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level.

Table 3: GDD Regression Results on Change in Growth of Earnings Per Worker in a Hurricane-Stricken County

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
Summer Seasonal Effect											
Coefficient:	-0.0283***	-0.0300***	-0.284***	-0.0283***	-0.0284***	-0.0283***	-0.0282***	-0.0282***	-0.0284***	-0.0284***	-0.0285***
P-value:	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Direct Effect of Hurricanes											
Coefficient:	0.0192***	0.0055	0.0066	0.0176**	0.0095	0.0198***	0.0262***	0.0192***	0.0208***	0.0223***	0.0206**
P-value:	*0.000*	*0.364*	*0.303*	*0.013*	*0.111*	*0.000*	*0.000*	*0.000*	*0.005*	*0.000*	*0.027*
Neighboring Effect of Hurricanes											
Coefficient:	-0.0093**	-0.0282***	-0.0105*	-0.0132**	-0.0129**	-0.0084*	-0.0096**	-0.0087**	-0.0247***	0.0041	-0.009
P-value:	*0.033*	*0.001*	*0.072*	*0.034*	*0.014*	*0.069*	*0.044*	*0.049*	*0.000*	*0.469*	*0.930*
Interaction of Direct and Multiple											
Coefficient:		0.0250**									
P-value:		*0.012*									
Interaction of Neighboring and Multiple											
Coefficient:		0.0022									
P-value:		*0.835*									
Interaction of Direct and Death Toll											
Coefficient:			0.0006*								
P-value:			*0.070*								
Interaction of Neighboring and Death Toll											
Coefficient:			-0.0004								
P-value:			*0.312*								
Interaction of Direct and Retired											
Coefficient:				0.0066							
P-value:				*0.614*							
Interaction of Neighboring and Retired											
Coefficient:				0.0140							
P-value:				*0.292*							
Interaction of Direct and Damage											
Coefficient:					0.0007						
P-value:					*0.256*						
Interaction of Neighboring and Damage											
Coefficient:					-0.0001						
P-value:					*0.921*						
Interaction of Direct and Election											
Coefficient:						-0.0047					
P-value:						*0.784*					
Interaction of Neighboring and Election											
Coefficient:						-0.0063					
P-value:						*0.650*					
Interaction of Direct and Early											
Coefficient:							-0.0198*				
P-value:							*0.060*				
Interaction of Neighboring and Early											
Coefficient:							-0.0062				
P-value:							*0.601*				
Second County Away Effect											
Coefficient:								-0.0046			
P-value:								*0.403*			
Interaction of Direct and Coastal											
Coefficient:									-0.0017		0.0038
P-value:									*0.860*		*0.752*
Interaction of Neighboring and Coastal											
Coefficient:									0.0246***		0.0079
P-value:									*0.005*		*0.511*
Interaction of Direct and Panhandle											
Coefficient:										-0.0167	-0.0204
P-value:										*0.100*	*0.204*
Interaction of Neighboring and Panhandle											
Coefficient:										-0.0321***	-0.0531***
P-value:										*0.000*	*0.000*
Interaction of Direct and C-P											
Coefficient:											0.0024
P-value:											*0.908*
Interaction of Neighboring and C-P											
Coefficient:											.0356**
P-value:											*0.046*
R^2	**0.1467**	**0.1544**	**0.1483**	**0.1469**	**0.1481**	**0.1468**	**0.1478**	**0.1468**	**0.1482**	**0.1503**	**0.1526**
F	**267.9**	**142.26**	**135.58**	**134.1**	**135.4**	**134**	**135.09**	**201.08**	**162.58**	**165.38**	**93.42**
n, groups	4746, 67	4746, 67	4746, 67	4746, 67	4746, 67	4746, 67	4746, 67	4746, 67	4746, 67	4746, 67	4746, 67

Note: Table reports selected coefficients of equations (10, 12, 16, 18, and 20) fit with QCEW data. See text for details. Included but not reported variables are the stand-alone dummy variables for each equation that correspond to each interaction term. *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level.

Table 4: GDD Regression Results of Hurricanes on Change in the following:

Coefficient:	**ln(employment)**	**ln(earnings)**
Summer Seasonal Effect		
Coefficient:	0.0163***	-0.0216***
P-value:	*0.000*	*0.000*
Direct Effect of Cat 1-3 Hurricanes		
Coefficient:	-0.0147***	0.0128**
P-value:	*0.010*	*0.027*
Neighboring Effect of Cat 1-3 Hurricanes		
Coefficient:	0.0023	-0.0451***
P-value:	*0.654*	*0.000*
Direct Effect of Cat 4-5 Hurricanes		
Coefficient:	-0.0476***	0.0435***
P-value:	*0.000*	*0.000*
Neighboring Effect of Cat 4-5 Hurricanes		
Coefficient:	0.0079	-0.0333***
P-value:	*0.374*	*0.000*
R^2	**.0241**	**.0451**
F	**23.19**	**44.13**
n, groups	4757, 67	4746, 67

Note: Table reports selected coefficients of equations (13 and 14) fit with QCEW data. See text for details.
*Significant at the 10% level
**Significant at the 5% level
***Significant at the 1% level

References:

Abadie, A., Diamond, A., and Hainmueller, J. (2007). "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Problem," NBER Working Paper 12831.

Angrist J. A. and Krueger A. B. (1999). "Empirical Strategies in Labor Economics," in O. C. Ashenfelter and D. A. Card, editors, *Handbook of Labor Economics*, 3A, Amsterdam: Elsevier, 1277-1366.

Avila, L. (1999). "Preliminary Report: Hurricane Irene," National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/1999irene.html.

Belasen, A. and Polachek, S. (2007). "When Oceans Attack: Using a Generalized Difference-in-Difference Technique to Assess the Impact of Hurricanes on Local Labor Markets," unpublished working paper, 2007.

Bertrand, M., Duflo, E., & Mullainathan, S. (2002). "How Much Should We Trust Differences-in-Differences Estimates?," NBER working paper 8841.

Beven, J. (2004). "Tropical Cyclone Report: Hurricane Frances," National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/2004frances.shtml.

Beven, J. (2006). "Tropical Cyclone Report: Hurricane Dennis," National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/pdf/TCR-AL042005_Dennis.pdf.

Beven, J. and Cobb, H. D. (2006). "Tropical Cyclone Report: Hurricane Ophelia," National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/pdf/TCR-AL162005_Ophelia.pdf.

Card, D. (1990). "The Impact of the Marial Boatlift on the Miami Labor Market," *Industrial and Labor Relations Review*, 43 (2), 245-257.

Climate.org (2004). "Brazil Hurricane," http://www.climate.org/topics/climate/brazil_hurricane.shtml.

Connolly, M. (2007). "Here Comes the Rain Again: Weather and Intertemporal Substitution of Leisure," unpublished working paper, 2007.

Ewing, B. T., and Kruse, J. B. (2006). "Hurricanes and Unemployment," *Natural Hazards Review*.

Ewing, B. T., Kruse, J. B., Thompson, M. A. (2007). "Twister! Employment Responses to the May 3, 1999, Oklahoma City Tornado," *Journal of Applied Economics* (forthcoming).

Google (2006). "Google Earth," http://earth.google.com.

Guimaraes, P., Hefner, F., & Woodward, D. (1993). "Wealth and Income Effects of Natural Disasters: An Econometric Analysis of Hurricane Hugo," *The Review of Regional Studies*, 23, 97-114.

Guiney, J. (1999). "Preliminary Report: Hurricane Georges," National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/1998georges.html.

Knabb, R. D., Rhome, J. R., & Brown, D. P. (2005). "Tropical Cyclone Report: Hurricane Katrina," National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/pdf/TCR-AL122005_Katrina.pdf.

Knabb, R. D., Brown, D. P., & Rhome, J. R., (2006). "Tropical Cyclone Report: Hurricane Rita," National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/pdf/TCR-AL182005_Rita.pdf.

Kubik, J. D. and Moran, J. R. (2003). "Can Policy Changes be Treated as Natural Experiments? Evidence from Cigarette Excise Taxes," NBER working paper 11068.

Lawrence, M. and Cobb, H. D. (2005). "Tropical Cyclone Report: Hurricane Jeanne," National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/2004jeanne.shtml.

Lucas, R. and Rapping, L. (1969). "Price Expectations and the Phillips Curve," *The American Economic Review*, 59 (3), 342-350.

Mayfield, M. (1995). "Preliminary Report: Hurricane Opal," National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/1995opal.html.

Mayfield, M. (1998). "Preliminary Report: Hurricane Earl," National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/1998earl.html.

Miguel, E. (2005). "Poverty and Witch Killing," *Review of Economic Studies*, 72 (4), 1153-1172.

National Oceanic and Atmospheric Association (1988). "Hurricane Florence," http://www.hpc.ncep.noaa.gov/tropical/rain/florence1988.html.

National Oceanic and Atmospheric Association (2006). "Hurricanes," http://hurricanes.noaa.gov/.

National Oceanic and Atmospheric Association (2006). "Retired Hurricane Names," http://www.nhc.noaa.gov/retirednames.shtml.

Padgett, G., Beven, J., & Free, J. L. (2004). Atlantic Oceanographic and Meteorological Laboratory, National Oceanic and Atmospheric

Association, http://www.aoml.noaa.gov/hrd/tcfaq/B3.html.

Pasch, R. J. (1996). “Preliminary Report: Hurricane Allison,” National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/1995allison.html.

Pasch, R. J. (1997). “Preliminary Report: Hurricane Danny,” National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/1997danny.html.

Pasch, R. J., Blake, E. S., Cobb, H.D., & Roberts, D. P. (2006). “Tropical Cyclone Report: Hurricane Wilma,” National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/pdf/TCR-AL252005_Wilma.pdf.

Pasch, R. J., Brown, D. P., & Blake, E. S. (2005). “Tropical Cyclone Report: Hurricane Charley,” National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/2004charley.shtml.

Pew Center on Global Climate Change (2006). “Global Warming and Hurricanes,” http://www.pewclimate.org/hurricanes.cfm/.

Rappaport, E. (1993). “Preliminary Report: Hurricane Andrew,” National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/1992andrew.html.

Rappaport, E. (1995). “Preliminary Report: Hurricane Erin,” National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/1995erin.html.

Skidmore, M. and Toya, H. (2002). “Do Natural Disasters Promote Long-Run Growth?” *Economic Inquiry*, 40, 664-687.

Stewart, S. (2001). “Preliminary Report: Hurricane Gordon,” National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/2000gordon.html.

Stewart, S. (2005). “Tropical Cyclone Report: Hurricane Ivan,” National Oceanic and Atmospheric Association, http://www.nhc.noaa.gov/2004ivan.shtml.

US Geological Survey (2006). “SOFIA: South Florida Information Access,” http://sofia.usgs.gov.

Waldman, M., Nicholson, S., Adilov, N. (2006). “Does Television Cause Autism?,” NBER working paper 12632.