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How Hurricanes Affect Wages and Employment in Local Labor Markets

By Ariel R. Belasen and Solomon W. Polachek*

Currently, a growing literature is emerging on estimating the impact of exogenous shocks using the difference-in-difference (DD) technique. Essentially, this technique compares the impact of an unexpected event in a particular locale (called the treatment/experimental group) to a location or set of locations (called a control group) similar to the experimental group in all respects except for the shock itself. One challenge many DD studies face is how to choose the control group, and there is now a growing literature on this (Joshua A. Angrist and Alan B. Krueger 1999; Jeffrey D. Kubik and John R. Moran 2003; and Alberto Abadie, Alexis Diamond, and Jens Hainmueller 2007). Another challenge is whether one can generalize one's results based on a single experimental group, as is typical for most DD analysis. This paper adopts a generalized-difference-in-difference (GDD) technique outlined in Ariel R. Belasen and Solomon W. Polachek (forthcoming) to examine the impact of hurricanes on the labor market. This technique incorporates *many* experimental as well as *many* control groups, and as such this approach addresses a number of shortcomings in current DD analyses. We find that earnings of the average worker in a Florida county rise over 4 percent within the first quarter of being hit by a major Category Four or Five hurricane relative to counties not hit, and rise about 1¼ percent for workers in Florida counties hit by less major Category One to Three hurricanes. Concomitantly, employment falls between 1½ and 5 percent depending on hurricane strength. On the other hand, the effects of hurricanes on neighboring counties have the opposite effects, moving earnings down between 3 and 4 percent in the quarter the hurricane struck. To better examine the specific shocks, we also observe sectoral employment shifts. Finally, we conduct a time-series analysis and find that, over time, there is somewhat of a cobweb, with earnings and employment rising and falling each quarter over a two-year time period.

I. Background

The effect of hurricanes on the labor market is not obvious. According to Robert Lucas and Leonard Rapping (1969), when people perceive a shock as having a temporary effect, they do 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 might 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.

Florida will generally witness about one hurricane during the typical six-month hurricane season, but there are years when Florida is not hit even once. Although hurricanes are not completely unexpected shocks to the state of Florida, each hurricane event is exogenous and unpredictable in that the exact timing and path of a hurricane cannot be determined a priori, nor can the degree of damage unleashed. Therefore, hurricanes can be used as an independent variable by comparing those counties that have been hit to the other counties that were not.

The hurricane data used in this analysis come from the National Hurricane Center of the National Oceanic and Atmospheric Administration (NOAA).[1] NOAA is a federal agency within the Department of Commerce which examines the conditions of the oceans and the

* Belasen: Department of Economics, Saint Louis University, 105 Davis-Shaugnessy Hall, 3674 Lindell Boulevard, Saint Louis, MO 63108 (e-mail: abelasen@slu.edu); Polachek: Department of Economics, State University of New York at Binghamton (Binghamton University), 1008 Library Tower, 4400 Vestal Parkway East, Binghamton, NY 13902 (e-mail: polachek@binghamton.edu).

[1] NOAA, http://www.noaa.gov/.

atmosphere. 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[2] and average quarterly earnings data from the Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages (QCEW)[3] were used, starting with the first quarter of 1988 and continuing through the fourth quarter of 2005.[4] The BLS surveys employers regarding their total wage bill and employment each quarter. We use these data for each county.

II. The GDD Estimation Model

The GDD model begins in similar fashion to the DD model in the sense that it compares outcome Y (actually, in our case two outcomes, employment denoted as N and earnings denoted as y) between treatment groups (H) and control groups ($\widetilde{H}$). Thus, for event H (in our case a hurricane), there are two possible outcomes: Y_H if a hurricane occurs and $Y_{\widetilde{H}}$ if it does not. Let $E[Y_{c,t}|\widetilde{H}]$ represent the expected value of Y if a hurricane does not occur in Florida county c at time t, and let $E[Y_{c,t}|H]$ be the expected value if the event does occur in county c at time t. Following Angrist and Krueger's (1999) specification,[5] the conditional means take the following form:

$$E[Y_{c,t}|\widetilde{H}] = \beta_c + \beta_t, \tag{1}$$

$$E[Y_{c,t}|H] = E[Y_{c,t}|\widetilde{H}] + \delta^*. \tag{2}$$

The parameter δ^* measures the exogenous shock when the two equations are differenced:

$$E[Y_{c,t}|H] - E[Y_{c,t}|\widetilde{H}] = \delta^* = \delta_c + \delta_t. \tag{3}$$

This δ^* difference effectively becomes the time- and event-averaged exogenous shock resulting from the set of events $\boldsymbol{H}$, taking into account characteristics of the counties hit. As such, it is composed of two parts: δ_c is the county-specific effect of hurricanes and δ_t is the time-varying effect of hurricanes. Both are identified in the GDD, given that c indexes each of the 67 Florida counties and that data on H entail all 19 hurricanes hitting Florida between 1988 and 2005.[6] As will be illustrated in the next section, we use equation (3) in three ways: first, in model (4) and (5), to get at the overall effect of H; second, in model (6) and (7), which represent a disaggregated version of (4) and (5), to get at H's effects by industry; and third, in model (8) and (9) to get at lagged effects of H.

III. Application of the Model

The study examines county-level employment (which we denote as N) as well as county-level average quarterly earnings per worker (which we denote as y) in the state of Florida. In order to measure the actual effects of hurricanes on employment and earnings, we control for additional factors that affect each county. Because Florida's economy has been growing rapidly over the last half-century, and every county in Florida has benefited from this growth, we control for the state trends of Florida by using GDD analysis to compare the average county affected by a hurricane to the average unaffected county.

To get at the effects of hurricanes, we incorporate hurricane severity, as well as hurricane location, particularly whether a county experienced a direct hurricane hit or was a neighboring county to one that was hit directly. In doing so, we split up the hurricanes into two subcategories based on the Saffir-Simpson Scale. Hurricanes that fall into Categories One, Two, or Three make up the low-intensity group

[2] Some employment data were available in a monthly format as well, and, whenever possible, monthly data were used for employment.

[3] BLS, http://www.bls.gov/.

[4] Hourly employment data would be preferable for this study; however, due to data limitations, total employment numbers were used instead.

[5] See Angrist and Krueger (1999) equations (18) and (19).

[6] Hurricanes are categorized according to the Saffir-Simpson Hurricane 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 George, 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.

Table 1—GDD Regression Results of Hurricanes on Change in the Average Growth Rate of Earnings and Employment in Hurricane-Stricken Counties Relative to Other Counties

	Direct effect		Neighboring effect	
Hurricane strength	Employment	Earnings	Employment	Earnings
Category One to Three	−0.0147***	0.0128**	0.0023	−0.0451***
Category Four to Five	−0.0476***	0.0435***	0.0079	−0.0333***

Notes: Table reports selected coefficients of equations (4) and (5) fit with QCEW data. Other variables include a seasonal adjustment variable. See text for details.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

($SS1$), and hurricanes in Categories Four or Five are placed into the high-intensity group ($SS2$). These variables now replace the hurricane variable (H) in the initial model. Thus, the model takes the following form, where $SS1$ and $SS2$ correspond to the two Saffir-Simpson groups, D refers to a directly hit county, I refers to a neighboring county, and variable X refers to whether the event occurred during the summer season:

$$(4) \qquad (\Delta \ln N_{ct} - \Delta \ln N_t) = \delta_{11} \Delta SS1^D_{ct} + \delta_{12} \Delta SS2^D_{ct} + \delta_{13} \Delta SS1^I_{cjt} + \delta_{14} \Delta SS2^I_{ct} + \alpha_1 X_c + \varepsilon_{ct};$$

$$(5) \qquad (\Delta \ln y_{ct} - \Delta \ln y_t) = \delta_{21} \Delta SS1^D_{ct} + \delta_{22} \Delta SS2^D_{ct} + \delta_{23} \Delta SS1^I_{ct} + \delta_{24} \Delta SS2^I_{ct} + \alpha_2 X_c + \varepsilon_{ct}.$$

Table 1 outlines the results of these regressions. High-intensity hurricanes have a much greater impact on earnings than the lower-intensity hurricanes, as they boost the growth rate of earnings per worker by 4.35 percent on average relative to workers in the average county. There is also a greater magnitude effect on employment, as it drops by 4.76 percent 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 percent decline in average wage growth relative to the typical county. Low-intensity hurricanes, on the other hand, will decrease employment by just 1.47 percent and boost earnings growth by 1.28 percent on average in directly hit counties. In neighboring counties, they will decrease the average earnings growth rate by 4.51 percent.

Second, we disaggregate (3) to subdivide the employment and earnings data across each industrial sector (Table 2). Equations (6) and (7) reflect the sector-specific effects of hurricanes, where S represents one of the five sectors of the labor market:

$$(6) \qquad (\Delta \ln N^S_{ct} - \Delta \ln N^S_t) = \delta_{11} \Delta H^D_{ct} + \delta_{12} \Delta H^I_{ct} + \alpha_1 X_c + \varepsilon_{ct};$$

$$(7) \qquad (\Delta \ln y^S_{ct} - \Delta \ln y^S_t) = \delta_{21} \Delta H^D_{ct} + \delta_{22} \Delta H^I_{ct} + \alpha_2 X_c + \varepsilon_{ct}.$$

Each industrial sector responds slightly differently from the aggregate model, though the weighted average of growth in employment and earnings appears to be about the same. Specifically, we find that employment and earnings move in the same direction for each of the industrial sectors, indicating that the hurricanes likely trigger demand shocks in the labor markets of directly hit counties. The construction and service sectors experience a positive shock, while manufacturing; trade, transportation, and utility (TTU); and finance, investment, and real estate (FIRE) experience downward shocks. In neighboring counties, we find significantly negative effects on earnings in the service and TTU sectors—also corresponding well to the aggregate model.

The differences between the individual sectors and the aggregate labor market appear to be driven by the heterogeneity of the county-

Table 2—GDD Regression Results of Hurricanes on Change in the Average Growth Rate of Earnings and Employment in Hurricane-Stricken Counties Relative to Other Counties by Industry

Industrial sector	Direct effect		Neighboring effect	
	Employment	Earnings	Employment	Earnings
Construction	0.0350	0.0463***	−0.0039	−0.0228
Manufacturing	−0.0031	−0.0264*	0.0099	−0.0031
Trade, transportation, and utilities	−0.0679*	−0.0279***	0.0061	−0.0083***
Service	0.0846*	0.0457***	−0.0039	−0.0044*
Finance, investment, real estate	−0.0041	−0.0849***	0.0038	−0.0029

Notes: Table reports selected coefficients of equations (6) and (7) using QCEW data. Other variables include a seasonal adjustment variable. See text for details.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

level labor markets. Certain counties are more agrarian and thus are less likely to be affected in the way that heavily industrialized counties are affected. Furthermore, as Belasen and Polachek (forthcoming) show, the Florida Panhandle is affected much differently from the rest of the state due to a major focus on the service sector in that region. When one accounts for the differences across counties, it becomes much more apparent that the individual demand shocks are in fact representative of the aggregate effect we find, in which earnings rise and employment falls.

For the third application of equation (3), we respecify the model to examine the lingering effects of hurricanes over time. Vector $\vec{\boldsymbol{H}}^D = (H^D_{ct}, H^D_{ct-1}, H^D_{ct-2}, \ldots)$ is used to represent the series of effects occurring when a hurricane strikes a county directly. Subscript c indicates that the hurricane is directly affecting county c, and the lag indicates how far back in time the hurricane hit:

$$(8)\quad (\Delta \ln N_{ct} - \Delta \ln N_t) = \Delta \vec{\boldsymbol{H}}^D_{ct} \vec{\boldsymbol{\delta}}_1 + \alpha_1 X_c + \varepsilon_{ct};$$

$$(9)\quad (\Delta \ln y_{ct} - \Delta \ln y_t) = \Delta \vec{\boldsymbol{H}}^D_{ct} \vec{\boldsymbol{\delta}}_2 + \alpha_2 X_c + \varepsilon_{ct}.$$

Figure 1 shows the regression results of a hurricane's effects in time t, as well as the lingering effects of that hurricane for 24 months following the storm.[7] As can be seen, a hurricane will immediately boost growth in earnings in the counties where it strikes, followed by an immediate downturn three months (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 percent above the level of growth for an average county. 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 percent lower than that of unaffected counties.

While this in no way indicates that earnings growth in a hurricane stricken county will permanently remain higher, nor that employment growth will remain permanently lower, 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 Paulo Guimaraes, Frank L. Hefner, and Douglas P. Woodward (1993) reported based on Hurricane Hugo. On the other hand, these findings are consistent with the existing literature of Bradley T. Ewing and Jamie B. Kruse (2005) and Ewing, Kruse, and Mark L. Thompson (forthcoming), which found that after a hurricane, earnings will jump immediately and then converge back toward 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.

IV. Conclusion

By using a GDD approach to compare changes in employment and earnings between counties hit and not hit by all 19 Florida hurricanes

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

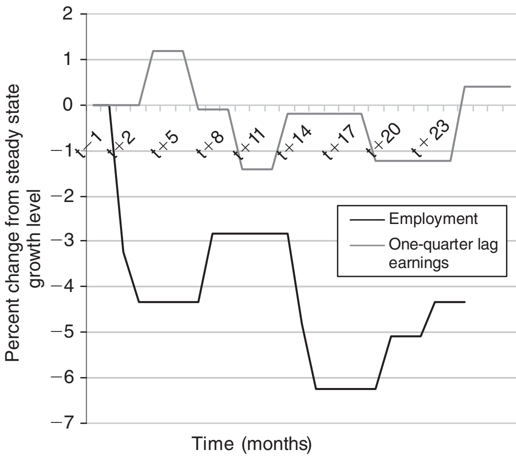

Figure 1. Effects of a Hurricane on an Average Directly Hit County over a 24-Month Period

(between 1988 and 2005), we examine how hurricanes affect the Florida labor market. Overall, we find that employment decreases by as much as 4.76 percent and earnings rise by up to 4.35 percent in counties directly hit, whereas neighboring counties face a decrease in earnings up to 4.5 percent, on average. As expected, more severe hurricanes have the largest effects. A micro study of five industrial sectors comprising the bulk of Florida's labor market reveals that hurricanes lead to demand shocks in the labor market, with the net results corresponding to the aggregate labor market effects. Over time, counties hit by hurricanes experience a positive net effect on earnings and a negative net effect on employment, but these effects dissipate over time. Whereas we apply the GDD technique to hurricanes, the approach is applicable to analyzing a wider range of exogenous shocks, such as earthquakes, tornadoes, tsunamis, and more.

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