

**When Oceans Attack:
Using a Generalized Difference-in-Difference Technique to Assess the Impact
of Hurricanes on Localized Taxable Sales**

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Abstract

This study identifies the exogenous impact of hurricanes on county-level taxable sales revenues in Florida using the Generalized Difference in Difference (GDD) econometric approach. The impact of hurricanes is calculated independently of seasonal trends as well as changes in the number of firms present in an average county. In the month in which a hurricane strikes a county, taxable sales revenues will decline between 6% and 10%, with the majority of this decline traceable to the direct impact of hurricanes on individual firms. Particular focus is also given to subsectors within the retail industry to examine the full reach of the economic loss due to hurricanes. Finally, it is shown that in the subsequent two years of rehabilitation, counties affected by hurricanes will face as much as a 35% average decline in taxable revenues. This decline in revenue can be explained, in part, to changes in the commercial make-up of a hurricane-stricken county.

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Introduction

Hurricanes regularly make landfall in the United States. The destructive power of hurricanes can wipe out thousands of lives and cause billions of dollars worth of infrastructure and private property losses as seen in the aftermath of Hurricane Katrina. The forced migration prompted by hurricanes also creates the potential for an area to lose its human capital. This loss of physical and human capital in a region can have significant short-term and possibly long-term effects on regional economic growth. In addition to their damage to physical and human capital, hurricanes also interrupt regional economic activity due to temporary lack of utility service, employee absenteeism, supply chain interruption, etc. Understanding the effects of hurricanes on a regional economy is critical to mitigate and recover the damage caused by hurricanes. Policy makers and local businesses could make projections of the potential impacts before actual disasters occur for mitigation strategies and develop better recovery plans (Thompson, 2009).

Most existing studies of hurricanes have been conducted in the framework of a singular event study. For example, Guimaraes, Hefner, and Woodward (1993) study the deviation that Hurricane Hugo caused South Carolina to take from its general trend of economic growth by using a with-and-without comparison of the economy. Ewing and Kruse (2001) study the effect of Hurricane Bertha on unemployment in Wilmington, North Carolina. Ewing, Kruse, and Thompson (2005) analyze the effect of Hurricane Bret on unemployment in Corpus Christi, Texas. Ewing and Kruse (2006) were among the first to examine a series of hurricanes within a singular framework, namely five hurricanes that struck Wilmington, NC during the late 1990s. They make use of a time series analysis to look at the effects of each of five hurricanes, both individually and collectively, on the unemployment rate of Wilmington, North Carolina.

These studies provide important insights on how a particular hurricane or a series of hurricanes affect a particular local economy. However, in general, the effects of hurricanes vary depending on the severity of the storm and the characteristics of the local economy. Consequently, the insights obtained through an analysis of one hurricane or multiple hurricanes on one local economy may not be able to generalize to a different hurricane or a different local economy. Moreover, these studies often fail to account for other macroeconomic changes that coincide with the dates of the hurricanes; and therefore could end up with biased estimates of the true impact of the hurricanes.

This paper adopts a generalized-difference-in-difference (GDD) technique to study the effects of hurricanes on the local economy that struck Florida between 1992 and 2006. Most hurricanes that strike the United States strike the Gulf States and the Southeastern States. Florida is a member of both subsets of states, and more hurricanes hit Florida than any other U.S. state. In the 15 year period between 1992 and 2006, a total of 18 hurricanes struck Florida, and none of Florida's 67 counties have escaped the effects of these hurricanes. Five of the six most damaging Atlantic hurricanes of all time have struck Florida over the course of this time period along with a number of relatively weak hurricanes as well.¹

Since each of these 18 hurricanes in our study varies in the exact timing, strength, path, and the degree of damage, and therefore can be analyzed independently or collectively, they provide us multiple random experiment groups (counties that have been hit by a hurricane in a given month) as well as multiple control groups (counties that have not been hit by a hurricane). By comparing those counties that have been hit to the other counties that were not across multiple hurricanes and time periods, we are able to study how the effect of a hurricane differs by both the characteristics of the hurricane and the characteristics of the local economy.

¹ See Table 1 in the Appendix for descriptive statistics of each hurricane in the sample.

Moreover, the estimation technique addresses the concern of any macroeconomic changes that coincide with the dates of the hurricanes by accounting for statewide trends in the data. In this way we can better isolate the effect of a hurricane as well as quantify its effect over time. Furthermore, hurricanes that strike a specific county directly can also have an impact on the economies of neighboring counties. Thus, we also use the GDD technique to study the spillover effects of hurricanes on neighboring counties as well.

Our analysis focuses on the impact of hurricanes on county-level taxable sales revenue, ranging from the sales of groceries, automobile, hotel rooms, utility, telephone services, to banking services. Taxable sales are not only key indicators of economic conditions but also important tax bases for state and local governments. Since most states and local governments base their budgets on their revenue forecasts, strong and viable tax revenue estimates are vital to regional economies recovering from disasters.² Understanding the effect of hurricanes on taxable sales help local policymakers and fiscal analysts make better revenue projection and better expenditure decisions to facilitate the recovery process. In addition to county-level total taxable sales, in view of the fact that tourism is a mainstay of the state's economy, it is also interesting to study how hurricanes affect Florida's tourism industries. Therefore, in addition to the overall sales of all categories subject to Florida sales and use taxes, we also study the taxable sales of two tourism-related industries, i.e. the taxable sales of restaurants and the taxable sales of bars and taverns.

The current study is closely related to Belasen and Polachek (2008; 2009) who use the GDD technique to examine a series of hurricanes that hit the state of Florida within a singular study to identify potential exogenous shocks in the labor market using quarterly data. The current paper complements their study by analyzing the impact of hurricanes on taxable sales.

² This is of particular importance in a state like Florida which does not have an income tax for its residents.

For states that do not collect state and local income tax, such as Florida, sales and usage taxes are the main sources of revenues for state and local governments. Therefore, taxable sales data are better indicators of state and local tax revenues for such states than employment and wages. Furthermore, the use of monthly county-level sales data in our analysis allows us to better distinguish short-term and long-term effects of hurricanes.

Examining Exogenous Shocks

The bulk of the past literature utilizes the difference-in-difference (DD) technique to isolate the economic impact of exogenous shocks. One of the most famous studies is Card's (1990) examination of the Mariel Boatlift which brought a large number of Cuban immigrants to Miami, Florida. In this study, Card showed that despite the large increase in the size of the labor force, there is little evidence to suggest a change in wages or unemployment, even among low-skilled workers. Using Miami as his treatment group, Card selected four cities (Atlanta, Houston, Los Angeles, and Tampa-St. Petersburg) that displayed similar demographic and economic growth characteristics to Miami between 1976 and 1984. Card found that the decrease in the unemployment rates once the boatlift began in Miami was insignificant relative to the comparison set of cities. Thus he concluded that the influx of Cuban immigrants did not impact the unemployment rate of Miami. However, Angrist and Krueger (1999) pointed out that Card's (1990) findings were inaccurate because the Miami labor market was not a good choice for this natural experiment. They look to an averted mass-immigration episode from Cuba that was to have taken place in 1994 and dub that the "Mariel Boatlift that did not Happen." Not surprisingly to them, they found that the mock boatlift had stronger findings than the actual boatlift – indicating that the choice of treatments and controls in Card (1990) left much to desire.

Angrist and Krueger (1999) showed that “different labor market trends can generate spurious findings in research of this type.”

A similar study using DD estimation, by Gautier, Siegmann, and Van Vuuren (2007), found that a murder in Amsterdam by a Muslim fundamentalist led to self-selected segregation of neighborhoods. After the murder, Muslims were more likely to buy (and less likely to sell) homes in neighborhoods with a higher share of Muslims than otherwise. Ironically, those neighborhoods experienced a decrease in the average housing prices relative to other neighborhoods despite the positive shift in demand. Thus they concluded that the Van Gogh murder was responsible for the change in housing prices.

Just as with the Card (1990) study, Gautier et al. failed to examine the change in overall trends in the market. They pointed out that even though only nine percent of Muslim minorities owned homes prior to the murder (in 2002), the rate of home ownership rose in Muslim neighborhoods, but what about elsewhere in Amsterdam? They also noted that the neighborhoods with high concentrations of Muslim minorities generally tend to be smaller, and therefore, lower cost homes. Putting both facts together, one can ascertain that if the rates of home ownership increased universally, perhaps the increase in demand led to a greater price increase in the native-Dutch dominated neighborhoods, and thus led to a lower relative-price for Muslim dominated neighborhoods.

Improving the Estimation Model

The common thread throughout most of the previous studies is a failure to account for overlying trends in the data. In addition, several studies have identification problems with regard to the treatment group versus the control group as Angrist and Krueger (1999) demonstrated, and

others overlooked potential endogeneity issues (Bertrand, Duflo, and Mullainathan, 2002; Kubik and Moran, 2003). For our purposes the endogeneity that we need to account for is related to the general trends in our data, both seasonally within each year, and across the full span of the data.

To that end, the GDD model first used in Belasen and Polachek (2008) improves upon the DD model by incorporating a multitude of events through which the average exogenous effect can be felt. Using a mean effect rather than a unique seemingly-exogenous shock minimizes the possible bias resulting from potential endogeneity between the variables. Additionally, the GDD model calls for a rotating pool of control groups and treatment groups such that likelihood of identification problems resulting from nonrandom sampling is eliminated. Each individual in that group can wind up as a member of the control group or the treatment group depending on the impact of the event. So essentially, DD is a special case of GDD in which only one event occurs at one given period of time. Of course, by generalizing the study via GDD, the probability that endogeneity has biased the results is minimized. Additionally, the identification problems will also be minimized because the control and treatment groups will be made up of the same individuals albeit at different points in time.

The GDD model begins in similar fashion to the DD model in the sense that a variable is chosen which takes the value of zero or one if a specific event occurs. Thus for event A there are two possible outcomes for the treatment group, one or zero; and one possible outcome for the control group, zero since the event never occurs for the control. Thus our variable of interest, Y , is different depending on the outcome of event A in time t . Let Y_0 represent the value of Y if the event does not impact individual c , and let Y_1 be the value if the event does occur for individual

c . Following Angrist and Krueger's (1999) specification,³ the conditional means take the following form with c representing the locale of interest:

$$E[Y_{0t} | c, A_t] = \beta_t + \gamma_c \quad (1)$$

$$E[Y_{1t} | c, A_t] = E[Y_{0t} | c, A_t] + E[\delta] \quad (2)$$

δ is the value assigned to the exogenous shock when the two equations are differenced. However, herein lays the difference between the two models. While the DD model assumes that this incident is isolated for one specific locale c , the GDD model makes no such assumption, such that c is a $(I \times k)$ vector of which an event A can occur for any of the k number of locales within that vector. At that specific period of time, t , in which A occurs, those locales affected by A will take a value of one and all other locales will take a value of zero. Furthermore, while event A is unique, there will be j such unique events such that A is a $(j \times I)$ vector. Thus, at any moment of time, a specific locale within c may take a value of one or zero depending on the outcome of A .

$$E[Y_{0t} | c_k, A_{jt}] = \beta_t + \gamma_k \quad (3)$$

$$E[Y_{1t} | c_k, A_{jt}] = E[Y_{0t} | c_k, A_{jt}] + E[\delta | k, j] \quad (4)$$

As with the DD model, the equations are differenced across time and across locales to differentiate the locales that were affected by event A from those who were not, however now

³ See Angrist and Krueger (1999) equations (18) and (19).

the GDD approach differs in that all of the locales that were unaffected will be used jointly to provide a more-balanced control group:

$$\{E[Y_t | c_k = 1, A_j = 1] - E[Y_{t-1} | c_k = 1, A_j = 0]\} - \{E[\bar{Y}_t | c_k = 0, A_j = 1] - E[\bar{Y}_{t-1} | c_k = 0, A_j = 0]\} = E[\delta^*] \quad (5)$$

The new estimate for the exogenous shock, δ^* , is the difference between the mean value of Y across time and between two sets of locales conditional on one set of locales effected by a unique event in a given period of time and the other consisting of the mean value of those locales unaffected by the event, given that several such events occur in the set of time $t = 1, \dots, T$. Therefore, δ^* effectively becomes the time and event averaged exogenous shock resulting from the vector of events A .

Data

The hurricane data used in this study come from the National Hurricane Center of the National Oceanic and Atmospheric Administration (NOAA).⁴ 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. NOAA reports that most hurricanes that strike the United States strike the Gulf States and the Southeastern States. Florida, as a member of both subsets of states, was hit by more hurricanes than any other US State over the time period of this study. In the 15 year period between 1992 and 2006, a total of 18 hurricanes struck Florida, and none of Florida's

⁴ National Oceanic and Atmospheric Administration, <http://www.noaa.gov/>

67 counties have escaped the effects of these hurricanes.⁵ Details regarding these 18 hurricanes can be found in Table 1 in the appendix. Beyond that, the paths of the hurricanes were traced following NOAA coordinates, and any county within a 100 km band of the path of the hurricane was considered to be directly hit by the hurricane.⁶ Those counties outside of that band but within a wider 500 km band were considered to be counties neighboring the hurricane, and would have faced a relatively weaker impact of the hurricane than those within the locus of destruction.

The gross sales data are collected from the Gross and Taxable Sales Reports by the Bureau of Economic and Business Research at the University of Florida⁷ which are prepared based upon data provided by the Florida Department of Revenue. The gross sales data include all sales reported monthly by businesses for sales and use taxes as required by the state law.⁸ The taxable sales data used in our analysis are county-level data, spanning the time period starting from January 1992 and continuing through December 2006. A summary of the sales data can be found in Table 2 in the Appendix.

Empirical Results

In adapting the GDD model to explain the impact of hurricanes on taxable sales, we are comparing sales in the average county affected by the hurricanes to the level of sales in the average unaffected county. Following the specification used in Belasen and Polachek (2009), our model takes the following form:

⁵ Note that five of the six most damaging Atlantic Hurricanes of all time struck Florida during this time period, as did some of the least damaging hurricanes. Therefore, this time period serves to provide a good mix of the potential economic disruption of hurricanes.

⁶ Belasen and Polachek (2008) defined the locus of destruction as the area within a 50 kilometer radius of the eye of the hurricane.

⁷ Bureau of Economic and Business Research, <http://bebr.ufl.edu/>

⁸ The classification for the businesses included in the study was drawn from the NAICS.

$$(\ln R_{it} - \ln R_t) = \alpha_1 S_t + \alpha_{2i}(F_{it} - F_t) + \alpha_{3i}H_{it}^D + \alpha_{4i}H_{it}^N \quad (6)$$

Here, $\ln R$ captures the natural logarithm of taxable revenue (in thousands of dollars) collected by private firms at the county level in Florida. We begin by taking the difference of the revenues collected in the average county (i) affected by a hurricane⁹ in month (t) from those collected in the average county that avoided being hit by the hurricane. This is regressed against the difference in the number of revenue-generating firms (F) in thousands in a given county from the average county. Furthermore, S represents a seasonal dummy variable used to control for the variability in the summer months,¹⁰ and the vector Z captures any individual county-level variability in sales revenue. Finally, a pair of vectors, H^D and H^N , capture the impact across time for hurricanes that directly impact county i , and that impact a county that is neighboring county i respectively. Finally, we difference the equation once again to achieve the change over time from period $t-1$ to period t , using Δ to denote that difference:

$$\Delta(\ln R_{it} - \ln R_t) = \alpha_1 \Delta S_t + \alpha_{2i} \Delta(F_{it} - F_t) + \alpha_{3i} \Delta H_{it}^D + \alpha_{4i} \Delta H_{it}^N \quad (7)$$

Note that now the time-invariant county-specific factors (Z) drop out of the equation. Thus, the factor which captures the majority of the difference between a given county and the average county is the difference in the quantity of revenue-generating firms. Since hurricanes may change the potential revenue of a firm, we may also see the impact of hurricanes within the

⁹ Further note that it in a few instances a single county has been hit by more than one hurricane in a single month. Upon analysis, however, the effects of being hit by multiple hurricanes within a single time period are statistically indifferent from those effects of being hit by a single hurricane.

¹⁰ The hurricane season encompasses the summer months, so it is particularly important to control for any seasonal variability during that time.

growth rate of firms in each county. Thus, to account for the potential that a hurricane may impact the revenues of a firm via a storm-induced consumption slow-down or a supply-side effect (such as a supply-chain interruption), we also choose to interact the number of firms with the hurricane variables as follows:¹¹

$$\begin{aligned} \Delta(\ln R_{it} - \ln R_t) = & \alpha_1 \Delta S_t + \alpha_{2i} \Delta(F_{it} - F_t) + \alpha_{3i} \Delta H_{it}^D + \alpha_{4i} \Delta H_{it}^N \\ & + \alpha_{5i} [\Delta(F_{it} - F_t) * \Delta H_{it}^D] + \alpha_{6i} [\Delta(F_{it} - F_t) * \Delta H_{it}^N] \end{aligned} \quad (8)$$

Our expectations are that hurricanes should diminish taxable revenues in stricken counties, both by diminishing the potential of new firms entering the area and by diminishing the demand for goods and services produced by the existing firms. Furthermore, as was found in Belasen and Polachek (2009), we expect to see a diminishing marginal effect of hurricanes as we travel further outside of the locus of destruction.¹² Therefore, the coefficients for each term containing hurricanes should be negative, and we would expect to see $|\alpha_{3i}| > |\alpha_{4i}|$ and $|\alpha_{5i}| > |\alpha_{6i}|$. Furthermore, with tourism down in the summer months, one would also expect to see revenues falling during this time for counties that are heavily reliant on tourism. However, since the same group of counties circulate between the control and treatment groups, it is particularly important to include a seasonal variable because most hurricanes also strike in the summer months and we want to isolate the hurricane effect from any overarching economic trends. Depending on the specific set of counties in the treatment group, the coefficient for the

¹¹ Note that while there is a relationship between the revenues of firms and the hurricanes as evidenced through the significant values for α_5 and α_6 , a regression examining the impact of hurricanes directly on the number of firms in a given county yielded insignificant results, likely indicating that outright firm closures are not the reason for this relationship.

¹² Belasen and Polachek (2008) found that stronger hurricanes had more significant effects on labor markets, likely due to a larger locus of destruction. Such a relationship was not found with regard to taxable revenues.

seasonal variable may take on a positive or negative value. Finally, as the number of firms in a county increases, one can reasonably expect the value of taxable revenues to increase, so $\alpha_2 > 0$. The results of this analysis can be seen in Table 3 in the appendix under the heading “Total Retail.”

Our findings reveal that the summer seasonal effect is not quite significant when it comes to sales revenues. Therefore, while previous studies have shown that the labor market tends to slow down in the summer months; taxable sales have an insignificant change over that period. Next, the coefficient for the firms shows that for every 1,000 more firms in a given county relative to the average county, taxable sales will increase by 5.6% on average. With an average taxable sales volume of \$264 million per county in the sample, the average gain here would be roughly \$15 million which represents a substantial variation in the tax base for a large county relative to a smaller one. Surprisingly, the hurricanes appear to have no significant direct effects on taxable sales. However, there is a highly significant indirect effect of hurricanes impacting individual firms. The interaction term reveals that hurricane-induced slowdowns will reduce revenues between 5.4% and 5.7% on average depending on the proximity of the hurricane. Unlike Belasen and Polachek (2009), we found no substantial difference related to the proximity of the county to the locus of destruction. That means that while firms located further away from the storm may not suffer as much structural damage as those caught directly in it, those firms may still find themselves facing slowdowns as demand for their goods and services drops following the hurricane.

To follow up with that point, we examine the impact of these hurricanes over time to see if there is a stronger lasting effect from hurricanes that directly hit a county relative to those that effects within a neighboring county, and finally to counties completely unaffected by hurricanes.

Our expectations are that hurricanes should diminish revenues in those counties that are stricken, however, over time we would expect to see those counties recover, and via relief funds, catch back up to the rest of the state within two years.¹³ Furthermore, since neighboring counties are only affected by strong winds and rain, and not the sheer devastation inflicted within the locus of destruction, we expect to see a diminishing effect as we move outside of the afflicted areas. The following equation captures this hypothesis:

$$\begin{aligned} \Delta(\ln R_{it} - \ln R_t) = & \alpha_1 \Delta S_t + \alpha_{2i} \Delta(F_{it} - F_t) + \Delta \vec{H}_{it}^D \vec{\alpha}_{mi} + \Delta \vec{H}_{it}^N \vec{\alpha}_{ni} \\ & + [\Delta(F_{it} - F_t) * \Delta \vec{H}_{it}^D] \vec{\alpha}_{pi} + [\Delta(F_{it} - F_t) * \Delta \vec{H}_{it}^N] \vec{\alpha}_{qi} \end{aligned} \quad (9)$$

Now the hurricane variables are replaced with vectors that measure the impact of a given hurricane strike on county i over the 24 months following the initial impact. We expect to see similar initial coefficients for α_{mi} , α_{ni} , α_{pi} , and α_{qi} as we found in the original specification. However, the impact should diminish over time as a county recovers from the initial impact of the hurricane. Effectively, this means the stricken county should begin to exhibit an economic recovery by the end of the two-year period. Therefore we expect to see that the net cumulative coefficients for α_{mi} , α_{ni} , α_{pi} , and α_{qi} should be equal to zero (i.e. no deviation relative to the average unaffected county) once the full extent of the hurricane's damage has been repaired. The results of this specification can be seen in Figure 1 below:

¹³ See Guimaraes et al. (1993); Ewing and Kruse (2005); Ewing et al. (2007); and Belasen and Polachek (2008; 2009) for a complete discussion on the significance of two years as the length of time for recovery.

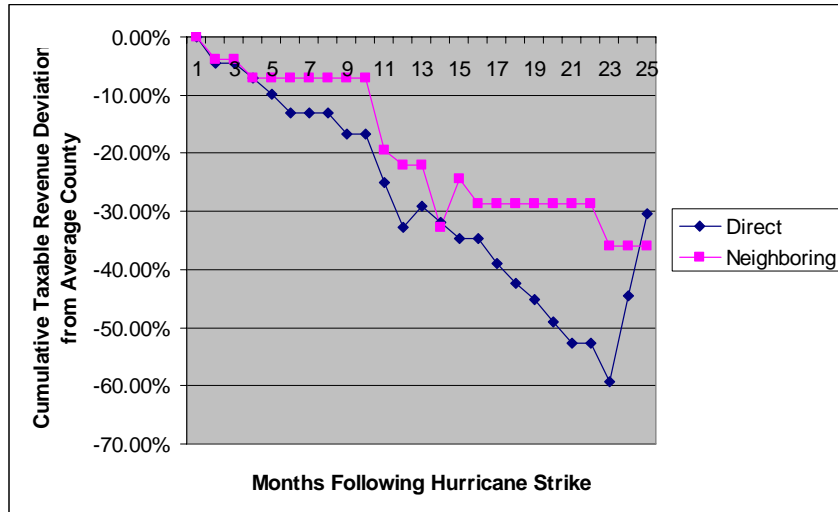


Figure 1: Cumulative Deviation in County-Level Taxable Revenues Due to Hurricane Strike

Our findings show mixed results regarding our hypotheses. First of all, the taxable revenues in a hurricane-stricken county do not fully return to the levels they were at prior to the strike after two years. This runs counter to the findings in the previous literature. With that said, the remainder of our hypothesis matched up fairly well with the empirical findings. Counties directly hit by hurricanes experience a 28.91% boost in revenues towards the end of the second year following the strike. Meanwhile, those counties that bordered the stricken county simply face a gradual downward trend. This likely indicates that disaster relief funds are generally allocated to the counties experiencing the most structural damage from the hurricanes. An examination of further months shows revenues in both sets of counties leveling off between 30% and 35% lower than the average unaffected county.

Extending the Analysis

To check for robustness of the findings we apply the same model to subsectors of the retail market that we believe will be particularly hard hit by a hurricane, namely the restaurant sector and the bar & tavern sector. Currently, only one in three Americans consume one or more meals

at home (Berry, 2002). Therefore we expect to see that a major reduction in consumer demand should heavily decimate restaurants and taverns. The framework for the model remains the same except that now we are looking specifically at those two subsectors of retail. Theoretically one should expect to see results that are similar in sign but different in magnitude. Thus if a hurricane strike decreases consumer demand and diminishes the availability of supply, we would expect to see negative coefficients for the direct impact of hurricanes as well as the interaction term between hurricanes and firms. Furthermore, if the results of the original specification are indeed correct then we should not expect to see signs of diminishing marginal impact as we examine counties outside of the locus of destruction. The results of this specification can be seen in Table 3 under the Restaurant and Bar & Tavern columns.

The findings reveal that the subsectors do indeed match up fairly well with the overall retail sector. Bars & Taverns are particularly hard hit by hurricanes, as it appears that there is less demand for their services. This appears to primarily be a demand-side effect because we do not see a similar pattern with the Restaurants, and one would imagine that a supply shock would be similar for both. Restaurants, meanwhile, do indeed exhibit signs of a diminishing marginal impact of hurricanes for counties located further from the locus, something we did not see with the Bars & Taverns. While this matched our original expectations it did not match the findings for the overall sector. All in all, the food service sectors appear to face between a 9.0% and 9.5% reduction in taxable revenues. In the restaurant subsector, this means the average impact of a hurricane is a \$2.1 million decrease in county-level taxable revenues. And looking specifically at the bar and tavern subsector, taxable revenues will decrease by close to \$300,000 in the average county hit by a hurricane.

As with the overall sector, we continue our analysis by examining the impact of hurricanes on the two subsectors over time. Again, we expect to see a diminishing impact as relief funds begin to restore commercial districts and residential life returns to normal. Just as with the entire retail sector, we expect to see a bounce back sometime in the second year; with revenues in hurricane-stricken counties moving back towards the mean level of revenues roughly 24 months after the hurricane strike. Figures 2 and 3 illustrate our findings.

What we have found is that both subsectors exhibit similar characteristics over time. For one, the end outcome is much different in these subsectors than it is in the overall retail sector. Whereas the overall retail sector appeared to fall between 30% and 35% after two years, the restaurant subsector falls between 10% and 15% and the bars & taverns fall between 20% and 25%. However, this decrease does not show any signs of abatement at the end of the two year cycle.¹⁴ This is the first finding showing such a prolonged downturn. It is apparent that the poor economic conditions on the ground affect daily luxury spending first and foremost.¹⁵ Secondly, both subsectors display a symmetric relationship between counties directly hit by hurricanes and their neighbors who did not face the brunt of the strike. Neighboring counties experience a growth rate in taxable revenues of just over 5% on average in their restaurant subsectors and nearly a 25% increase in their bar & tavern subsectors. Thus it appears that the bulk of the economic activity related to these two subsectors moves away from the stricken county and outwards towards neighboring counties. This finding runs contrary to the finding that for the overall retail sector the decline in taxable revenues in directly hit counties is roughly equaled by its neighbors. Therefore we can hypothesize that while certain portions of retail move away from stricken regions; other portions tend to move in.

¹⁴ Examining the impact over a lengthier duration shows recovery occurring in the 9th quarter following the initial hurricane strike.

¹⁵ This is similar to the downturns these subsectors face in prolonged recessionary periods.

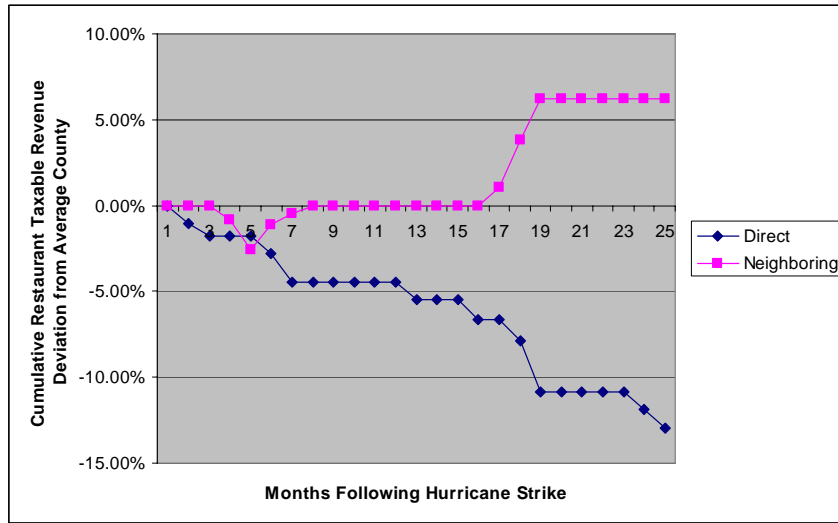


Figure 2: Cumulative Deviation in County-Level Restaurant Taxable Revenues Due to Hurricane Strike

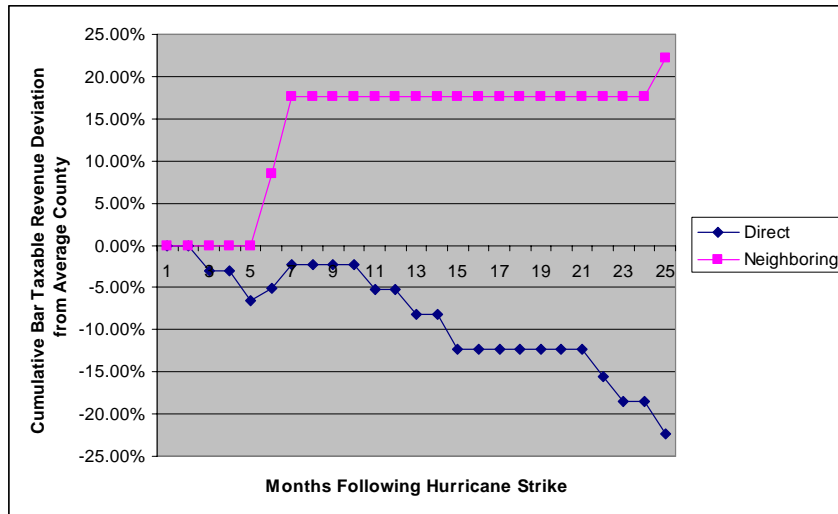


Figure 3: Cumulative Deviation in County-Level Bar & Tavern Taxable Revenues Due to Hurricane Strike

Conclusion

Florida finds itself in a unique position among other Southeastern US states in that it faces a threat from hurricanes both from the Gulf of Mexico as well as from the North Atlantic Ocean. This study identified the average impact of a hurricane on Florida’s taxable sales revenue. Since the bulk of Florida’s state revenues come from sales and usage taxes, a disruption of this income

stream can be particularly damaging to state-level services. The study showed that a hurricane strike can reduce revenues by nearly six percent overall; with revenues in some sectors facing declines closer to ten percent. Furthermore, while revenues do recover over time, there is evidence that the level of taxable revenues in a hurricane-stricken will not ever be as high as they would have been had the county avoided being hit by the hurricane. An examination of economic subsectors reveals that this long-term decline is likely due to a fundamental change in the economic makeup of the retail sector in hurricane-stricken counties. This indicates that the optimal recovery policy and effort should differ across sectors. A potential extension would be to examine further subsectors to identify this pattern. The findings could also potentially be improved by surveying firms independently to identify the behavioral choices made by each firm during the post-hurricane recovery period. Perhaps this would reveal a more efficient technique for policymakers to follow when pursuing recovery efforts.

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Appendix

Table 1: Hurricane Descriptive Statistics

Name (Retired)	Synoptic Lifecycle		Damage to FL in Millions	Deaths in FL	Wind Speed	Average Rainfall	Magnitude
<i>Andrew</i>	August	1992	\$40,500	44	175 mph	5"-7"	5
<i>Allison</i>	June	1995	\$1.1	0	75 mph	4"-6"	1
<i>Erin</i>	August	1995	\$0.5	6	87 mph	5"-12"	1
<i>Opal</i>	September	1995	\$4,600	1	115 mph	5"-10"	3
<i>Danny</i>	July	1997	\$134 total to US	0	80 mph	2"-7"	1
<i>Earl</i>	September	1998	\$104	2	92 mph	6"-16"	1
<i>Georges</i>	September	1998	\$406.8	0	103 mph	8"-25"	2
<i>Irene</i>	October	1999	\$1,000	8	75 mph	10"-20"	1
<i>Gordon</i>	September	2000	\$11.9	1	75 mph	3"-5"	1
<i>Charley</i>	August	2004	\$14,800	29	150 mph	5"-8"	4
<i>Frances</i>	September	2004	\$10,200	37	105 mph	10"-20"	2
<i>Ivan</i>	September	2004	\$9,200	19	130 mph	7"-15"	3
<i>Jeanne</i>	September	2004	\$7,900	3	121 mph	8"-13"	3
<i>Dennis</i>	July	2005	\$2,400	14	120 mph	10"-15"	3
<i>Katrina</i>	August	2005	\$1,700	14	81 mph	5"-15"	1
<i>Ophelia</i>	September	2005	\$77.2 total to US	1	80 mph	3"-5"	1
<i>Rita</i>	September	2005	\$12,500 total to US	2	115 mph	2"-4"	2
<i>Wilma</i>	October	2005	\$22,700	31	120 mph	7"-12"	3

Appendix

Table 2: Taxable Sales Revenue Summary Statistics (in Millions of Dollars)

	n	Mean	Standard Deviation
Overall Retail	12,788	\$263.67	\$495.64
Restaurants	12,757	\$23.45	\$42.83
Bars & Taverns	11,179	\$2.95	\$4.60

Table 3: Generalized Difference-in-Difference Regression Results of the Impact of Hurricanes on the Natural Logarithm of Taxable Sale Revenue in the Average County in Florida

Coefficient:	Total Retail	Restaurants	Bars&Taverns
Summer Seasonal Effect			
<i>Coefficient:</i>	0.0122	-0.0070	-0.0071
<i>P-value:</i>	0.125	0.447	0.434
Difference in Number of Firms (1,000's)			
<i>Coefficient:</i>	0.0561***	0.1260***	0.0500***
<i>P-value:</i>	0.000	0.000	0.000
Direct Effect of Hurricanes			
<i>Coefficient:</i>	-0.0062	0.0022	-0.0499*
<i>P-value:</i>	0.820	0.944	0.098
Neighboring Effect of Hurricanes			
<i>Coefficient:</i>	-0.0152	-0.0135	0.0129
<i>P-value:</i>	0.511	0.611	0.635
Interaction of Firms and Direct			
<i>Coefficient:</i>	-0.0538***	-0.0954***	-0.0403**
<i>P-value:</i>	0.000	0.006	0.049
Interaction of Firms and Neighboring			
<i>Coefficient:</i>	-0.0574***	-0.0642	-0.0396*
<i>P-value:</i>	0.001	0.239	0.089
R²	.4718	.4838	.2097
Wald	3277.54	5389.35	833.19
n (groups)	12,780 (67)	12,728 (67)	10,926 (67)

Note: The net effects were comprised of individual lagged effects that were significant at the 10% level or higher.

***Significant at the 1% level

**Significant at the 5% level

*Significant at the 10% level