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# Harmful Algal Blooms and Tourism: The Economic Impact to Counties in Southwest Florida\*

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**Abstract:** The most recent red tide bloom in the summer of 2018 served as a wake up call to many in the Gulf region of Florida. The algal bloom decimated the coast, killing off scores of fish and marine life. As beaches were forced to close, tourists and residents alike were no longer producing usual economic activity on the shorelines. This, however, has happened before. We consider four major blooms from the past twenty years, two in 2005, one in 2006, and the aforementioned bloom in 2018. All lasted for over three months and had significant impacts on the economy. We examine the effects of two industries, the lodging and restaurant sectors, to determine the magnitude of losses in taxable sales caused by red tide. Using a difference-in-differences model, we compare taxable sales in counties affected by red tide to those that were unaffected. We find that affected counties produce 5-7 percent and 1.5-2.5 percent less in the lodging and restaurant sectors, respectively. If red tide blooms become more frequent and persistent, losses for coastal businesses could also continue to grow. Policy and strategy to mitigate economics losses must take into consideration the harmful effects of these algal blooms.

**Keywords:** difference-in-differences, economics, harmful algal blooms (HABs), *Karenia Brevis*, red tide  
**JEL Codes:** L83, M38, Q51

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## 1. INTRODUCTION

Harmful algal blooms (HABs) are almost always present in the Gulf of Mexico, usually harmless and at low concentrations (Roberts, 1979; Pierce et al., 2005; Pierce and Henry, 2008). However, as the microscopic algae creep towards the shores of Western Florida, they have the potential to become a natural disaster, as damaging as hurricanes or lightning heavy tropical storms that Southwestern Florida is typically known for. *Karenia brevis*, the algae responsible for the effects of HABs in southwest Florida, can cause mortalities in almost all of marine life, ranging from massive fish kills across species, to sharks, dolphins and even

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sea birds (Flewelling et al., 2005; Pierce and Henry, 2008). Humans can be affected as well, either through consumption of shellfish that has become poisoned by the brevetoxins from *karenia brevis*, or via respiratory difficulties when aerosolized brevetoxins can cause itchy throats and lungs, and shortness of breath (Plakas et al., 2002; Fleming et al., 2005; Pierce et al., 2005).

The harmful effects of HABs can force beach closures, fishing restrictions, and even reduce seafood and shellfish consumption.<sup>1</sup> For a state heavily reliant on revenue from tourism such as Florida, a bloom severe enough to result in these restrictions could drive away visitors and revenue from the coast. Additionally, a persistent bloom that lasts for many days, even months, might force shutdowns long enough that firms by the shore cannot recuperate and suffer significant losses in revenue. HABs, and more specifically red tides, are increasing in frequency and both severity and persistency over time (Van Dolah, 2000; Pierce and Henry, 2008). If the most recent bloom in 2018 was a prelude to what is becoming the norm, business reliant on tourism could face increasing expected losses. This paper studies the losses by these firms in the presence of red tide and compares the results to unaffected or less affected firms through a difference-in-differences model.

## 2. LITERATURE REVIEW

The economic effects of HABs have been studied previously. There is quite a bit of literature that has found statistically significant negative effects of red tide on the local economies in Southwest and Northwest Florida. Until recently, much of the research lacked a rigorous statistical approach, relying more on survey data and summary statistics than econometric analysis. Tester et al. (1991) looked at changes in seafood value during the presence of red tide. Hoagland and Scatasta (2006), Adams et al. (2008), Hoagland et al. (2009), and Anderson et al. (2012) estimated annual losses by looking at aggregated data from multiple industries within the economy. While these losses were valid results, the field needed more reliable results.

Larkin et al. (2007) were perhaps the first to implement a time series model on the impact of red tide on the economy, something that Nordhaus (1999) suggested might be an appropriate model for a natural disaster. Larkin et al. (2007) studied a small, coastal area on Ft. Walton and Destin beaches in Northwest Florida. They used taxable sales from the restaurant and lodging sector to estimate monthly losses when red tide is present. They found that in months where the beaches experienced red tide, the coastal firms in the lodging and restaurant sectors lost about 30 percent of their sales. Morgan et al. (2009) conducted a similar study for three beachfront restaurants in Manatee County. They found daily losses on average of 14 percent for the restaurants when red tide was present on that day. More recently, Bechard (2019) used a time series ARIMA model for county level taxable sales in Sarasota County, and found that tourism related sectors such as lodging and restaurants lost on average 15 percent and 2 percent, respectively, in monthly sales, when red tide was present.

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<sup>1</sup>See <https://myfwc.com/research/redtide/statewide> for information on closures, restrictions, and consumption in Florida.

In all previous studies, red tide has been used as a single-instance dummy variable within a time series model. Its sudden blooms can shock an economy for a brief period of time. However, rarely has this field considered the effects of multiple red tide blooms over a long period of time, which is something that this study is the first to do. Four blooms in particular were significantly devastating to the Southwest Florida counties. The early 2005, late 2005, 2006 and 2018 blooms lasted, at their peak, for over three months at extremely high and dangerous levels. Due to this continued impact on the counties and the economies, this paper is the first to implement the time series data from the counties and treat it as panel data. This allows us, with the correct modeling, to perform a difference-in-differences approach between affected and unaffected counties.

As previously mentioned, natural hazard studies are sparse for the economic impacts of red tides. However, another hazard that plagues the environment and subsequent tourism, oil spills, have been examined for quite some time. Similar to harmful algal blooms, oil spills can negatively impact coastal tourism due to contaminated ocean water. Internationally, studies found that oil spills can cause millions of dollars in tourism revenue to be lost. The Exxon-Valdez oil spill in March of 1989 caused revenues to decline by over 10 percent in tourism related sectors such as recreational fishing and lodging (Cohen, 1993). In the 2000's, the Prestige oil spill off the coast of Galicia, Spain in 2002, the Don Pedro sinking and subsequent oil leakage on Ibiza's shores in 2007, and the Hebei-Spirit oil spill in Taean County of South Korea all caused losses in the millions, about 8-12 percent in lost revenue for affected hotels and restaurants (Garza-Gil et al., 2006; Cheong, 2012; Cirer-Costa, 2015). Ritchie et al. (2014) found that the BP oil spill in 2010 cost Gulf states such as Texas, Louisiana, Alabama, and Florida a combined \$1.6 billion dollars in lost tourism revenue.

The findings on the impacts of oil spills provide great insight into the impacts that red tide blooms could have on local economies. A less drastic, but still environmentally impactful study is the construction of wind turbines along the shores. Lang et al. (2014) used a difference-in-differences model to study the impact of wind turbines on the local economies' tourism sector. Although not relevant in terms of the question at hand when dealing with HABs, the authors showed that difference-in-differences models are a good way to estimate the impacts that a changing environment has on tourism related sectors in an economy. The difference-in-differences methodology used in Lang et al. (2014) can easily be translated to a persistent red tide event that temporarily changes the environment for several months at a time.

### 3. DATA

#### 3.1. Taxable Sales Data

Gross taxable sales data were collected at the county level for each reporting county in the state of Florida. The data is publicly available from the Florida Department of Revenue.<sup>2</sup> Each county breaks down its total taxable sales into economic sectors based on the type of business and type of good or service produced. While there is heterogeneity in terms of what sectors a county has and therefore reports, a great number of counties report sectors that are

<sup>2</sup>Data is available at: [http://floridarevenue.com/taxes/pages/colls\\_from\\_7\\_2003.aspx](http://floridarevenue.com/taxes/pages/colls_from_7_2003.aspx).

of significant interest to this study. This paper looks at two tourism related sectors: lodging and restaurants. The motivation to study these sectors came from the fact that the health of county economies in Florida are heavily dependent on revenue generated from tourism (Larkin et al., 2007; Morgan et al., 2009; Bechard, 2019).

The taxable sales data for each sector and for each county were collected from the Florida Department of Revenue for a sixteen-year (202 month) time period, from January 2002 to December 2018. The data is publicly available and reported monthly. The monthly taxable sales data was adjusted for inflation by using the Bureau of Labor Statistics monthly Consumer Price Index (CPI) to bring all taxable sales into 2002 numbers, the base year of the study. Again, due to the heterogeneity in counties, not all counties had monthly taxable sales data for the lodging and restaurant sectors. These counties were omitted from the study.

### 3.2. Algal Bloom Data

Using a general consensus amongst university scientists and government funded programs, in combination with water sampling data, it was evident that during the 202 month period of the study, there were four major blooms; severe in the concentration of *karina brevis* cells in the water, and persistent, lasting for multiple months in a row.

#### *Early 2005*

The first severe HAB began in January of 2005, and persisted for three months, before dying out in March of that same year.<sup>3</sup> This was the beginning of one of the worst years for red tide in history.<sup>4</sup> What began about 20 miles off the coast of St. Petersburg in Pinellas County as the size of a car, the bloom grew to over a mile long in size and affected over 150 miles of Florida coast, from St. Petersburg to Naples, leaving millions of tourists and residents to clean up the mess and suffer the consequences (Tavel, 2018).

#### *Late 2005*

After a brief respite from red tide (although there were a few minor and short-lived blooms) in the spring and early summer of 2005, another severe and persistent bloom struck in August. Comparable in size and damage of its predecessor, this bloom lasted four months, until subsiding in late November. These two blooms bookended what was the worst year of red tide presence ever recorded. It left, as scientists say, a “dead zone” the size of Rhode Island on the ocean floor of the Gulf.<sup>4</sup>

#### *Fall 2006*

Similar to the late 2005 bloom, this HAB began in August and lasted until late November. It was arguably even worse in severity than the 2005 blooms, as some southwestern counties experienced at least 15 days of red tide each of the four months.<sup>5</sup> Sarasota County in particular was victim to three months in a row of 19 days or more of red tide, from August through October.

<sup>3</sup>Harmful Algal Bloom data is available at: <https://habsos.noaa.gov/>.

<sup>4</sup>For a timeline of red tide events, see <https://www.heraldtribune.com/news/20060716/red-tide-timeline>.

<sup>5</sup>For more information, see <https://service.ncddc.noaa.gov/website/AGSViewers/HABSOS/maps.htm>.

### Fall 2018

An early June bloom was the first of many warning signs for scientists that the summer of 2018 would be a disastrous one. With this irregular start, Florida was devastated for six months in a row by a persistent HAB that did not seem to go away under any circumstances. As cooler waters came in, the bloom finally gave out in late November, but not before it left a lasting impression on all of Florida and left many worrying for the future of the Gulf.

## 4. MODEL SELECTION

### 4.1. Time Transformations

To construct a difference-in-differences model, it is helpful to first transform the time period slightly. Because there are multiple periods of treatment, a new variable was created, “months relative to bloom.” This allows for all of the blooms to start at the same treatment time. Once a bloom is considered to be over, the count of months before the next bloom begins again. For example, all months before January 2005 are negative in sign. December 2004 is equal to -1, November 2004 is equal to -2, and so on, all the way to the beginning of our data. January 2005 is equal to 0, February 2005 is equal to 1, and March 2005 is equal to 2. All positive values signify a persistent bloom occurrence in that month. Once this bloom ended in March of 2005, April 2005 was given a value of -4, since it would be four months until the next bloom occurred, in August of that same year. The same process was done throughout the remaining years.

### 4.2. Previous OLS Models

Due to the somewhat stochastic nature of time-series data, it can be difficult to soundly run Ordinary Least Squares Regressions on the data without transforming it, so as to make it stationary (Baum, 2006). Additionally, without accounting for correlation between lagged values of the dependent variable, the results on the coefficients can become inconsistent and biased, due to omitted variable bias (Kmenta, 1986; Verbeek, 2012). Bechard (2019) uses lagged values of taxable sales to study red tide impacts on Sarasota County. Following Baade et al. (2012), taking the natural log of the taxable sales data and incorporating lagged values as independent variables provides a very nice OLS regression with a very good fit to the data, with R-squared values over 95 percent. Using their model as a guideline, consider a similar model with just one county and a dummy variable for a “treated” month of red tide:

$$y_{ct}^* = \beta_0 + \beta_1 x_1 + \beta_2 redtide_t + \sum_{p=1}^p \varphi_p y_{c,t-p}^* + \sum_{m=1}^{11} \alpha_m S_m + \epsilon_t \quad (1)$$

where  $y_{ct}^*$  is a transformation of a taxable sales sector in a given county  $c$ , in time period  $t$ .  $X_1$  is a vector of macroeconomic shocks aside from red tide blooms that still need to be controlled for in the model. We then have our dummy variable for a month that experienced red tide, similar to Bechard (2019). We also have lagged values of the taxable sales for that sector and monthly fixed effects.

### 4.3. Discussion on Lagged Values

There is much debate as to whether the inclusion of lagged values will result in detrimental bias to the other independent variables. All previous studies agree that lagged variables bias the coefficients of themselves, and thus there should be no interpretation made using these results. However, the argument then lies in whether to incorporate them in the model or exclude them all together. The inclusion of lagged variables could help partially alleviate serial correlation, something that almost always exists when using time series panel data, which most difference-in-differences models use (Bertrand et al., 2012). Incorporating them could lead to bias in other independent variables and make the coefficients of other regressors inconsistent. Excluding lagged values will introduce omitted variable bias, as past values are almost certain to be a good predictor of future values.

Baade et al. (2012) argued that exogenous variables are not biased by lagged dependent variables. Kiviet (1995) and Judson and Owen (1999) found that even in large time series panel data, using lagged variables can create a relatively small bias on other coefficients in the model. Achen (2000) and Keele and Kelly (2006) also found evidence of lagged variables creating bias in the other regressors. The latter three papers all show that lags can create downward bias, so in terms of the study on red tide impacts, this implies that the coefficients will be biased towards zero. Due to the inability to obtain the exact amount of bias, models will be run with and without lags, to get a range of values of the impact of red tide on taxable sales and to determine if the bias on the lags is enough to cause concern with model selection.

### 4.4. Difference-in-Differences Model

As mentioned earlier, this model previously fit Florida county taxable sales data very well (Baade et al., 2012). From here, a difference-in-differences model can be created by augmenting equation (1) slightly. If we treat our relative months before a bloom as the pre-treatment time period, and our months after the beginning of and to the end of the bloom as our intervention period, along with a treatment and control group, we arrive at the following model:

$$y_{ct}^* = \beta_0 + \beta_1 x_1 + \sum_{p=1}^{12} \varphi_p y_{c,t-p}^* + \mu_1 T_{ct} + \mu_2 R_{ct} + \mu_3 T * R_{ct} + S_m + S_w + \omega_c + \epsilon_t. \quad (2)$$

Now,  $y_{ct}^*$  is some transformation of a taxable sales sector in a given county  $c$ , in time period  $t$ .  $X_1$  is still a vector of macroeconomic shocks aside from red tide blooms. This includes month-year fixed effects for two hurricanes, Hurricane Charley (August 2004) and Hurricane Irma (September 2017), both of which made landfall in Southwest Florida. That is, we have two binary variables equal to 1 for August 2004 and September 2017 respectively across counties, and zero otherwise.  $\varphi_p$  are coefficients of lagged values of the transformed taxable sales sector for a given county. The lags go back 12 months, which was optimally chosen to minimize the Akaike Information Criterion (AIC). Given that each county has a different number of optimal lags for a sector ranging from 10 to 14 months, it was decided that for the

cross-sectional data, 12 months (the past year) of lags is sufficient to capture any variation in taxable sales that is due to the recent past trends of that sector. Lastly, we have county, monthly and yearly fixed effects,  $\omega_c$ ,  $S_m$ , and  $S_w$ , respectively.

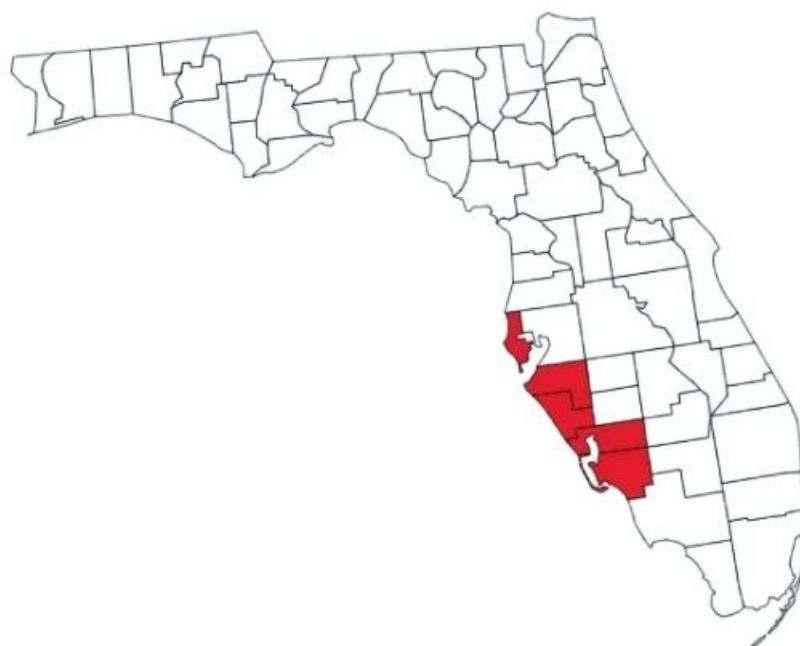
The new independent variables added to equation (2) are the difference-in-differences dummy variables,  $T$  and  $R$ , and the interaction term  $T * R$ .  $T$  is a dummy variable equal to 1 if the monthly observation came during a bloom, that is, if it is in the “treatment” period of the timeframe.  $R$  is a dummy variable equal to 1 if that county is considered to be in the “treatment” group, in that this county experienced the three plus months of continuous red tide exposure during the four blooms. The interaction term  $T * R$  is equal to 1 if the county was considered to have experienced red tide and this continued experience came during the time period of the four blooms considered in this study. The coefficient on  $T * R$ ,  $\mu_3$ , is the coefficient of interest. This will be the difference in marginal changes in taxable sales between the treated group and control group, during the times of the blooms.

Stated previously, when dealing with time series it is necessary to make the data stationary. This can be done in a variety of ways. Taking the natural log of the data is one way, and another common transformation is taking the 12-month growth rate, or percent change, of the data (Baumann et al., 2012; Bechard, 2019). This is done to not only deal with seasonality between months, but to also remove unit roots from the series. For this study, just the 12-month growth rate transformations were conducted. The natural log transformation violated the parallel trends assumption, necessary for difference-in-differences models, which will be explained later. When using lags the parallel trends assumption failed, but the assumption held without lags. Since model selection is still ambiguous, the natural log transformation was not used in the main results but was used later as a robustness check.

#### 4.5. Treatment Group

The next consideration comes when deciding on the “treatment” group. Although red tide blooms throughout the years have affected counties from the Florida Panhandle down to the Florida Keys, there are five counties that immediately stand out as bearing the brunt of all red tides. Pinellas, Manatee, Sarasota, Charlotte, and Lee Counties all have been significantly impacted by persistent red tides. In the time frame of the four blooms considered in this study, there were 39 times when a county experienced ten days or more of red tide during these months. Pinellas accounted for five of these months, Manatee five as well. Sarasota accounted for 11 of these months, Charlotte eight and Lee County five. Remarkably, out of the 39 times there was a month with ten days or more of red tide, a staggering 34 times it happened in one of these five counties (87 percent). The remaining five instances occurred in Monroe County, but since this county does not report consistent lodging data, it was omitted from the treated group. Furthermore, eight times, a county experienced more than 16 days of red tide in a month (essentially half of a month with red tide presence) during the four blooms. All eight (100 percent) occurred in one of these five counties. For this reason, these five counties were considered as the treated group. All other counties (58 of them) that had lodging and restaurant data were considered part of the control group. Figure 1 shows the counties classified as treated on a map of the whole state, and Table 1 shows summary statistics comparing the treated and control counties.

**Figure 1: Treated Group of Counties Along Florida's Gulf Coast**



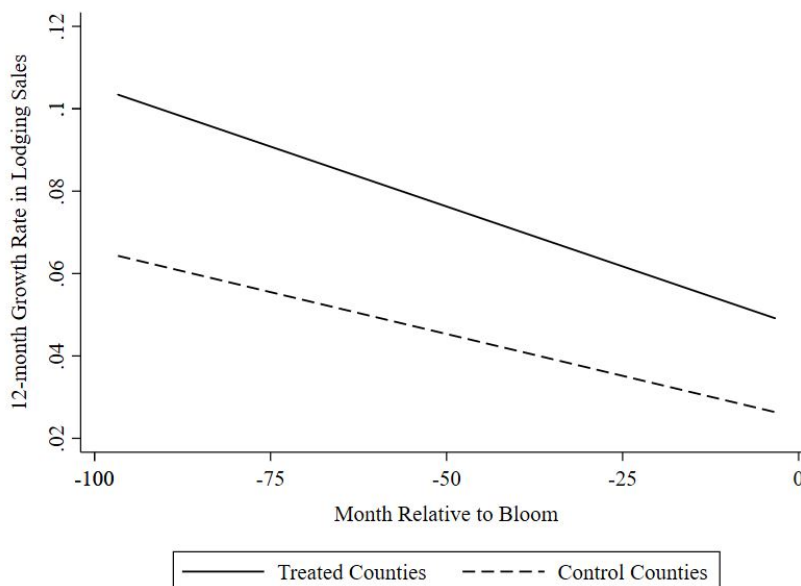
The southwest region of Florida highlighted above that will be counted as the “treated” group. From North to South, these counties are: Pinellas, Manatee, Sarasota, Charlotte, and Lee. This area has experienced more red tide blooms during the last 16 years than anywhere else in the state.

**Table 1: Summary Statistics (Standard Errors in Parenthesis)**

	Pre-Treatment Means		Difference in “Pre” Means	Post-Treatment Means		Difference in “Post” Means
	Treated	Control		Treated	Control	
12-month growth rate (lodging)	0.033 (0.273)	0.048 (0.276)	0.016 (0.010)	-0.031 (0.136)	0.063 (0.317)	0.095** (0.040)
12-month growth rate (restaurant)	0.030 (0.056)	0.031 (0.125)	0.002 (0.004)	0.021 (0.056)	0.046 (0.134)	0.024 (0.017)

Note: Average values are taken from all counties that had observations for all months, given a certain a sector. For lodging, the sample size was 890, 9873, 65, 743 for columns 1, 2, 4, and 5 respectively. For restaurants, the sample size was 890, 10976, 65, 806 for columns 1,2,4,5 respectively. Standard errors below in parentheses in the difference in means column. \*, \*\*, and \*\*\* represent significance at the 10 percent, 5 percent, and 1 percent level of significance, respectively.



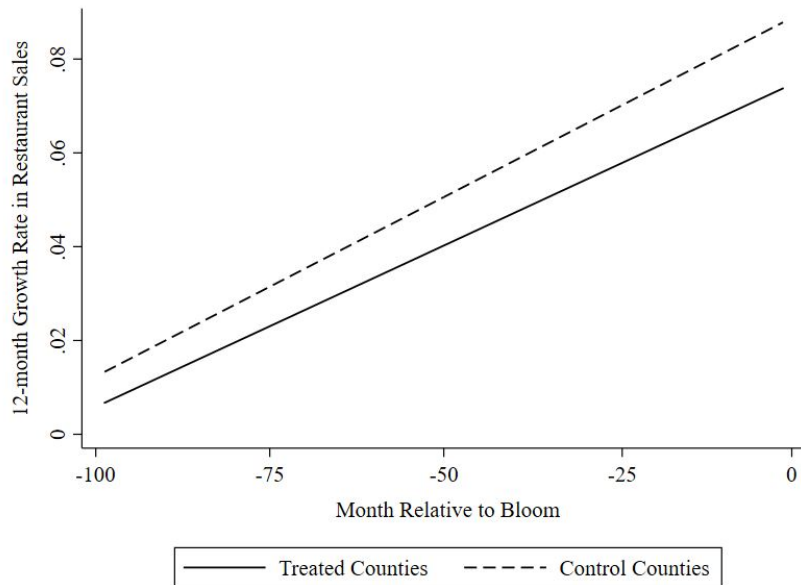
**Figure 2: Lodging Sales Pre-Treatment Trends**

Graphical representation of the parallel trends assumption before conducting a difference-in-differences model. The 12-month growth rate lodging sales pre-treatment trends for treated and control counties are presented. The solid line represents the group of treated counties, and the dash represents the control counties.

## 5. RESULTS

A key assumption of the difference-in-differences model is “parallel trends,” which requires that the treated and control group have similar trends in taxable sales in the time periods before the blooms. If this assumption does not hold, then the difference in sales might not only come from the treated time period during blooms. Differing trends before blooms in untreated time periods implies that something other than red tide impacted sales and thus our results would be invalid. This assumption must first be tested before any valid conclusions can be made about coefficients in the difference-in-differences model. When we test the assumption (again just for the 12-month growth rate), using either sector of taxable sales, with or without lags, the results show no statistically significant differences in trends, even at the 10 percent level. Figures 2 and 3 show the pre-treatment trends for both the lodging and restaurant sectors. Thus, we can safely assume that parallel trends hold, and the difference-in-differences model is viable.

Using equation (2), the difference-in-differences model can be tested. All of the models include county and year fixed effects. The inclusion of county fixed effects will omit the coefficient on “treatment,”  $\mu_2$ , in the results. All variation in treated groups will be controlled for within the context of county fixed effects, so these variables become co-linear with  $\mu_2$ , and forces it to be omitted. The coefficient of interest,  $\mu_3$ , will still have the same interpretation and validity as stated above, in that it is the expected difference in monthly changes

**Figure 3: Restaurant Sales Pre-Treatment Trends**

Graphical representation of the parallel trends assumption before conducting a difference-in-differences model. The 12-month growth rate restaurant sector sales are presented. The solid line represents the group of treated counties, and the dash represents the control counties.

for treated counties compared to untreated ones during months of a bloom. When using the 12-month growth rate, seasonal and monthly time-invariant characteristics are captured in that change and are no longer needed as controls in the model. Depending on whether lags are included or not, the omitted year is 2004 and 2003, respectively. For the model with lagged variables, due to the high number of lags (12), 2003 data could not be used since there is no lagged data before 2002. All models use standard errors clustered by county. This helps account for heteroskedasticity and autocorrelation, something that affects the consistency of coefficients in time-series panel data if uncontrolled for (Bertrand et al., 2012). First, the lodging sector was tested and results are shown in Table 2. The restaurant sector was then tested and the results are shown in Table 3.

## 6. DISCUSSION

### 6.1. Lodging Sector

First, consider the results of the lodging sector in Table 2. Looking at the 12-month growth rate when using lags, the results suggest a 7.15 percent deficit in monthly sales for those counties affected by red tide, compared to others spared from the effects. As Judson and Owen (1999), Achen (2000), and Keele and Kelly (2006) suggest, the bias was slightly downward due to the use of lags. Without lags, the results show affected counties producing 7.79 percent less in sales than unaffected counties during the months of a bloom. The monthly

**Table 2:** Difference-in-Differences Results (Lodging Sector)

VARIABLES	(1)	(2)
	12-month growth rate	12-month growth rate
Hurricane Irma	-0.00821 (0.0329)	0.00585 (0.0298)
Hurricane Charley	-0.00482 (0.0359)	-0.0112 (0.0406)
T (time =1, during bloom)	0.000553 (0.0122)	-0.00197 (0.0119)
R (treat = 1, treated county)	-	-
TR (treat = 1, time = 1)	-0.0715*** (0.0202)	-0.0780*** (0.0223)
Constant	0.0853*** (0.0225)	0.0175 (0.0215)
Use of Lags?	yes	no
Month Fixed Effects?	no	no
Year Fixed Effects?	yes	yes
County Fixed Effects?	yes	yes
Observations	10,773	11,571
R-squared	0.196	0.038

Notes: Standard errors are shown below in parentheses and are clustered at the county level. \*, \*\*, and \*\*\* represent significance at the 10 percent, 5 percent, and 1 percent level of significance, respectively.

results are similar to previous studies, such as Larkin et al. (2007) and Bechard (2019) which also found negative impacts to sales. Perhaps very important to policy and risk aversion strategies, is the interpretation of these coefficients. Considering the results from the model with lags, for the average month in a treated county that generates over \$28,400,000, a 7.15 percent decrease results in \$2,030,600 of lost revenue. Since this average treatment effect changes, this is the expected difference in monthly lodging sales. With that said, since persistent blooms can last as shown for over three months in a row, losses in lodging can accrue month by month and put a business severely behind expected profits. The monthly results are similar to Larkin et al. (2007) and Bechard (2019).

## 6.2. Restaurant Sector

Next, the results of the restaurant sector in Table 3 present a similar picture as the lodging sector. Slightly different than the lodging sector, a few more counties had restaurant data, so the total number of counties used was 67, instead of 63. When using lags, affected counties

**Table 3:** Difference-in-Differences Results (Restaurant Sector)

VARIABLES	(1) 12-month growth rate	(2) 12-month growth rate
Hurricane Irma	-0.0301** (0.0118)	-0.0330*** (0.0115)
Hurricane Charley	0.0326** (0.0136)	0.0457*** (0.0130)
T (time =1, during bloom)	0.00206 (0.00423)	0.00273 (0.00484)
R (treat = 1, treated county)	-	-
TR (treat = 1, time = 1)	-0.0178** (0.00720)	-0.0225*** (0.00813)
Constant	0.0464*** (0.00629)	0.0487*** (0.0111)
Use of Lags?	yes	no
Month Fixed Effects?	no	no
Year Fixed Effects?	yes	yes
County Fixed Effects?	yes	yes
Observations	11,897	12,737
R-squared	0.282	0.071

Notes: Standard errors are shown below in parentheses and are clustered at the county level. \*, \*\*, and \*\*\* represent significance at the 10 percent, 5 percent, and 1 percent level of significance, respectively.

bring in on average 1.78 percent less in restaurant sales than unaffected counties. Without lags, the results are very similar, suggesting a 2.25 percent deficit for these counties compared to the control group. The results for the restaurant sector are very similar to Morgan et al. (2009) and Bechard (2019). Again, although 1.78 percent to 2.25 percent might not seem like an “economically” significant amount, for an average month in a treated county that generates over \$53,300,000, 2.25 percent less in revenue amounts to \$1,199,250 in lost profits. With persistent blooms, these effects can accrue over time. For a bloom that lasts, say three months, that could result in a roughly 2 percent decrease in sales each month, amassing more losses the longer a bloom persists.

### 6.3. Implications

Economic intuition suggests that the results should be negative, so our findings have a sign consistent with neoclassical theory. Given the shock to the coastal economy when a bloom occurs, one might expect demand for beach use and beach-related services to go down. With

**Table 4:** Difference-in-Differences Results, Using Natural Log Transformation

VARIABLES	(1) Lodging Sector	(2) Restaurant Sector
Hurricane Irma	-0.0401 (0.0313)	-0.0369*** (0.00939)
Hurricane Charley	0.0253 (0.0275)	0.0317*** (0.0101)
T (time =1, during bloom)	-0.0147* (0.00830)	-0.00383 (0.00320)
R (treat = 1, treated county)	-	-
TR (treat = 1, time = 1)	-0.0557*** (0.0208)	-0.0159** (0.00633)
Constant	1.192*** (0.443)	1.310*** (0.390)
Use of Lags?	yes	no
Month Fixed Effects?	yes	yes
Year Fixed Effects?	yes	yes
County Fixed Effects?	yes	yes
Observations	11,562	12,735
R-squared	0.819	0.825

Notes: Standard errors are shown below in parentheses and are clustered at the county level. \*, \*\*, and \*\*\* represent significance at the 10 percent, 5 percent, and 1 percent level of significance, respectively.

beaches no longer available and seafood consumption banned, complementary goods to beach activity, such as coastal lodging and dining, experience a decrease in demand as well, thus the loss in revenue occurs. Reliant so heavily on tourism, red tide can greatly impact the economy beyond just beach closures. Statewide, \$24.3 billion is spent by tourists on lodging, and another \$20.2 billion on food and beverage services. Tourism is responsible for over 1.5 million jobs, leading to \$54.7 billion in paid wages, and generates \$11.4 billion in state and local taxes,<sup>5</sup> When the revenue is no longer being generated due to a harmful bloom, the effects that hurt hotels and restaurants then in turn negatively impact people's earned wages, and government spending. As a whole, welfare can decrease significantly. The results suggest that mitigation of these blooms should be at the forefront of policy decisions.

<sup>5</sup>See <https://www.visitflorida.org/>.

## 7. ROBUSTNESS CHECKS

What the results show, for both sectors, is that the lagged dependent variables used as regressors have little bias. Although there is a slight downward bias, it is almost negligible. Additionally, the R-squared values are much higher using the lagged model. This suggests that perhaps it is better to incorporate the lagged values into the model. The bias created when they are included is not severe enough to forgo explaining taxable sales as if the current value is uncorrelated with past values. Essentially, we knowingly take on this minimal bias from including lags, rather than risking a larger omitted variable bias by excluding past values.

### 7.1. Natural Log Transformation

Since we find that incorporating lagged values creates minimal bias in the results, we look at another transformation of the data. As stated before, taking the natural log of sales is another common way to make the data stationary. It also has the very nice property that it is interpreted as the percent change in monthly sales. Therefore, our coefficient of interest,  $\mu_3$ , will still be the percent difference in monthly sales for treated counties compared to untreated counties during persistent blooms. Recall that the transformed natural log model without lags failed to uphold the parallel trends assumption, but the model using lags holds. Thus, only the model using lags was run for both sectors. We add monthly fixed effects since this transformation does not control for that, with the omitted month being January. The results are shown in Table 4. We find with this transformation, the results suggest treated counties experienced 5.57 percent less in lodging sales, and 1.59 percent less in restaurant sales. These results are very similar to the ones found using the 12-month growth rate. This implies that the results are robust across similar transformations, and that the true values of the deficits in sales are consistent with our findings.

### 7.2. Reduced Sample Size

Another series of robustness checks can be performed to strengthen the validity of these results. A common robustness check is to reduce the sample size and analyze the new results. If the results from the difference-in-differences model are robust, a reduced sample should have little to no effect. When using the whole sample, between the Fall 2006 bloom and Fall 2018 bloom, there were 138 months. Thus, originally, we have data stretching back as far as 138 months relative to the start of a bloom. We reduce this sample size several times, and the results still hold and remain statistically significant. We run the reduced sample on both lagged and unlagged 12-month growth rates, and the lagged natural log transformation model. The results are shown in Table 5. We reduce the sample size twice. Instead of allowing months before a bloom to range as far back as 138, we shorten the pre-treatment period to 100 months, and 50 months. In either case, the results remain statistically significant and differ only slightly around their original values from the full sample. This suggests that the results are robust and not idiosyncratic based on the sample size, or in this case, the length of the time period studied.

**Table 5:** Robustness Check with Reduced Sample Size

<i>Panel A: Shortening Sample to a maximum of 100 months before bloom</i>						
VARIABLES	Lodging Sector			Restaurant Sector		
	(1)	(2)	(3)	(4)	(5)	(6)
	12-month growth rate	12-month growth rate	Natural Log	12-month growth rate	12-month growth rate	Natural Log
T (time =1, during bloom)	-0.000711 (0.0122)	-0.00339 (0.0121)	-0.0156* (0.00854)	0.00166 (0.00415)	0.00211 (0.00493)	-0.0069** (0.00318)
R (treat = 1, treated county)	-	-	-	-	-	-
TR (treat = 1, time = 1)	-0.070*** (0.0206)	-0.069*** (0.0220)	-0.055** (0.0220)	-0.021*** (0.00693)	-0.025*** (0.00764)	-0.018*** (0.00622)
Observations	8,392	9,166	9,157	9,310	10,150	10,148
R-squared	0.167	0.014	0.820	0.244	0.037	0.839
<i>Panel B: Shortening Sample to a Maximum of 50 Months before Bloom</i>						
VARIABLES	Lodging Sector			Restaurant Sector		
	(1)	(2)	(3)	(4)	(5)	(6)
	12-month growth rate	12-month growth rate	Natural Log	12-month growth rate	12-month growth rate	Natural Log
T (time =1, during bloom)	-0.00106 (0.0123)	-0.00471 (0.0123)	-0.0157 (0.00970)	0.00123 (0.00412)	0.00186 (0.00494)	-0.00551 (0.00369)
R (treat = 1, treated county)	-	-	-	-	-	-
TR (treat = 1, time = 1)	-0.066*** (0.0226)	-0.053** (0.0212)	-0.049** (0.0233)	-0.020*** (0.00658)	-0.021*** (0.00702)	-0.018*** (0.00644)
Observations	5,320	6,094	6,085	6,010	6,838	6,836
R-squared	0.131	0.014	0.806	0.228	0.029	0.838

Notes: Standard errors are shown below in parentheses and are clustered at the county level. \*, \*\*, and \*\*\* represent significance at the 10 percent, 5 percent, and 1 percent level of significance, respectively. All regressions still include a constant and controls for Hurricane Charley and Hurricane Irma but are omitted here for brevity. All regressions include county and year fixed effects. Columns 3 and 6 have monthly fixed effects as well. Columns 1, 3, 4 and 6 include 12 months of lagged values as independent variables, whereas columns 2 and 5 do not use lagged values as regressors.

### 7.3. Testing Unaffected Sectors

A third type of robustness check can be used to ensure that the negative impacts on sales were in fact due to the red tide blooms and not some other macroeconomic factor. In theory, other sectors of the economy in treated counties that are not as susceptible to the effects of red tide should not see any difference in sales compared to unaffected counties. To test this, we look at two other sectors, thought to be unaffected by red tide blooms; the home furniture sector and clothing apparel sector. These two sectors were chosen for two reasons.

**Table 6:** Robustness Check With Sectors Unaffected by Red Tide Blooms

VARIABLES	Furniture Sector			Clothing Sector		
	(1)	(2)	(3)	(4)	(5)	(6)
	12-month growth rate	12-month growth rate	Natural Log	12-month growth rate	12-month growth rate	Natural Log
T (time =1, during bloom)	0.0499*** (0.0122)	0.0459*** (0.0165)	0.00152 (0.00669)	0.0391*** (0.0144)	0.0323*** (0.0116)	0.0327*** (0.00618)
R (treat = 1, treated county)	-	-	-	-	-	-
TR (treat = 1, time = 1)	-0.0171 (0.0191)	-0.0223 (0.0259)	0.00316 (0.0128)	-0.0150 (0.0201)	0.0118 (0.0306)	0.00794 (0.0179)
Observations	9,358	10,066	10,066	9,199	9,907	9,907
R-squared	0.421	0.169	0.784	0.478	0.018	0.806

Notes: Standard errors are shown below in parentheses and are clustered at the county level. \*, \*\*, and \*\*\* represent significance at the 10 percent, 5 percent, and 1 percent level of significance, respectively. All regressions still include a constant and controls for Hurricane Charley and Hurricane Irma but are omitted here for brevity. All regressions include county and year fixed effects. Columns 3 and 6 have monthly fixed effects as well. Columns 1, 3, 4 and 6 include 12 months of lagged values as dependent variables, whereas columns 2 and 5 do not use lagged values as regressors.

First, the majority of the counties had data for both furniture and clothing sectors. Many other sectors were missing data elsewhere, so these two were most abundant in terms of observations. Second, it is fairly easy to see why these two sectors should not be affected by red tide blooms. Furniture and clothing sales are not heavily reliant on tourists, but more so on full time residents. Their shopping behaviors are not thought to be affected by red tide, especially since these firms are usually indoors, and away from the coast, negating any of the effects from the blooms.

Using the same regressions as lodging and food, we test the difference in difference models for these two sectors. The results are shown in Table 6. As expected, we see no statistically significant difference in sales between affected and unaffected counties. This lends credence to the belief that the impacts to the lodging and restaurant sectors were due to a harmful bloom, and not some other macroeconomic event that would have affected more than just these sectors.

## 8. CONCLUSION

The four major harmful algal blooms off the coast of Florida between 2002 and 2018 caused significant damage for affected counties. Using two sectors of the economy that are associated with tourism, we find monthly sales during persistent blooms decreased significantly for affected counties when compared to counties unaffected by the blooms. When looking at the lodging sector, affected counties experience anywhere from 5-7 percent less in sales than unaffected counties. The affected counties also see a 1.2-2.5 percent deficit in restaurant sales during these blooms. These results are very robust, across similar transformations, sample



size, and sector of interest. As blooms become more severe and more persistent, losses for firms within these affected counties could start to become catastrophic. The inability to recuperate the losses from the effects of the blooms could be exacerbated if more months are affected and hence more days are keeping tourists and vital revenue away.

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