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Red tide at morning, tourists take warning? County-level economic effects of HABS on tourism dependent sectors

Andrew Bechard

Department of Environmental and Natural Resource Economics, University of Rhode Island, 45 Upper College Rd, Kingston, RI 02881, United States

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ABSTRACT

A tourism dependent state such as Florida relies on its environment and climate to attract visitors and generate revenue. HABs can certainly have an impact on the coastal waters of the Gulf, but does this necessarily drive away tourist related activity? To determine not only if the impact of HABs is significant, but also at what magnitude, a time series econometric model was used to study effects of persistent and severe blooms on counties in Southwestern Florida, particularly Sarasota County, hit hardest by blooms in 2006 and 2018 that lasted multiple months. Lodging and restaurant sectors of the economy were found to have monthly losses of 15% and 1.75% respectively, during months when red tide was present. Neighboring counties unaffected by severe blooms did not experience significant losses to these sectors. These results support the intuition that effects of HABs reach far beyond the waters of the Gulf, and as red tide grows in frequency and severity, more economic loss could lie ahead.

1. Introduction

On its own, it would be the world's sixteenth largest economy with a GDP of over 1 trillion dollars (Bureau of Economic Analysis, 2018). As the "Sunshine State" continues to grow in popularity each year and draw in tourists from all around the United States and the world, Florida seeks to maximize the returns from its location in the ever desirable climate of the Southeast. Sporting one of the longest contiguous coastlines in the U.S, the warm weather, coupled with clear blue seas and skies in Florida draws locals and visitors alike to its shorelines, where those who hail from probably colder parts spend over twenty-two billion dollars a year on beach related tourism (Waymer, 2010). Very few states can compete with the tourism that Florida generates, and for counties and a state that rely on its environment, it can be very harmful if even a disruption in this ecosystem occurs.

Enter *karenia brevis*, a miniscule marine alga that blooms and thrives in high salinity regions of the Gulf of Mexico, and could be the suspect behind the death of not only a whale shark, but hundreds of thousands of other fish that could not evade its grasp (Diaz, 2018). This dinoflagellate is almost always present in the waters of southwest Florida, but when it starts to bloom are the times that a microscopic creature can create massive problems (Roberts, 1979). These high concentrations of *karenia brevis* in a relatively small area are defined in a larger set with all possibly dangerous algae known as Harmful Algal Blooms (HABs). The effects of HABs, and more specifically red tide, reach far beyond the waters of the Gulf, and can infiltrate and negatively impact county economies in the process (Pierce and Henry, 2008). This paper examines economic sectors in the coastal county of Sarasota, Florida through its taxable sales to determine the extent and severity of the financial impact red tide blooms have caused.

Sarasota County is located on the southwest coast of Florida, and is home to over 417,000 residents and a temporary landing spot for an estimated 90,000 tourists a year (Sarasota County Government, 2019). Over 60% of the population, and more than half of all hotels and lodging accommodations are concentrated to within 10 miles of the coast (United States Census Bureau, 2018). Siesta Key, voted annually as one of the top beaches in the world is located in Sarasota County, along with countless others such as Venice, Nokomis, Lido and the aptly named Turtle Beach. Reliant so heavily on its climate, red tide blooms have affected many that were hoping for a beach getaway. From January of 2002 to November of 2018, Sarasota County experienced five months (9/2005, 8/2006, 10/2006, 8/2018, 11/2018) where red tide was present for 20 or more days in a given month (NOAA, 2019). The majority of these came during two major red tide blooms, one in the fall of 2006, and the more recent and infamous one in the summer of 2018, that persisted for over 4 months. When blooms of this persistence and severity occur, fishing operations are shut down, oceanside restaurants must close up outdoor dining to avoid airborne effects of red tide, and shorelines scored with deceased fish as far as the eye can see force the closing of beaches (Florida Fish and Wildlife Conservation Commission

E-mail address: andrew_bechard@uri.edu.

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(FWC), 2018). These blooms surely impact business and life in the coastal county, and as previous studies have shown, the tourist service industries are hit the hardest.

2. Literature review

Case studies on harmful algal blooms have found negative effects on the economy before. Throughout the years, Adams et al. (2008); Anderson et al. (2012), and Hoagland and Scatasta (2006, 2009) have estimated national losses in the ballpark of 50 million dollars annually due to HABs. Recently, a more thorough approach has been conducted by Larkin and Adams (2007), and Morgan et al. (2009) in attempt to rigorously and empirically study the effects of red tide blooms on northwest Gulf counties for coastal restaurants and hotels in Destin and Ft. Walton beach, and Manatee County respectively. The 2007 paper finds around 30% declines in monthly sales, whereas the 2009 paper finds daily losses of about 13% on average when red tide was present. As Larkin and Adams (2007) state, time series applications on red tide effects have been scarce. While the more recent studies have used a semblance of time trends and time series processors, this paper will use a more rigorous and in depth ARIMA model to better fit the data, which has been useful in studying other mega-events. Instead of a time trend, the ARIMA model uses lagged terms of the dependent variable and error term, something that previous literature has lacked, and additionally, using county-wide data, this paper allows for studies of control "groups". We will be able to see the effect of firms or other counties that were not affected by red tide, and how they influence the results of the sectors in the county economy, to ensure that there was not some other macroeconomic event exclusive of red tide that possibly could result in decreased sales. While a time series study was conducted by Adams et al in 2000 using Sarasota data, no significant effects were found (Morgan et al., 2009). Since 2000, in terms of data collection, "luckily" there have been more severe and persistent blooms (2006, 2018) to allow for more observations of treated months, giving more power to the coefficient on the variable of interest thus making the data a good fit for use of the ARIMA model.

Baade et al., (2007, 2008, 2010), and Baumann et al., (2012, 2017, 2018) have longed used the ARIMA model to measure the impact of a mega-event in a relatively small area. While there are no set criteria for what defines a mega-event, we are going to consider red tide blooms as one. Though it does not spark as much interest as other mega-events (see Olympics), the onset of a persistent and severe bloom can cause just as much of a shock in the economy. For many large-scale sporting events such as the World Cup or Olympics, the ARIMA model is useful to capture a sudden spike or change in economic activity. Using the same dataset as was used in this paper, the authors were able to study the impacts of major sports teams on gross taxable sales for the Florida counties (Baumann et al., 2018). Mega-event studies are not always restricted to the world of sports, however. They also were able to study the effects of Hurricane Andrew in 1993 as a way to predict what might happen following Hurricane Katrina in 2005 (Baumann et al., 2018). As they state, taxable sales are a great way to measure the health of the economy and can easily reveal any sudden or sharp changes (Baumann et al., 2018). Intuitively, impacts and effects from red tide will be sudden, and around the time frame of the bloom, easily identifiable in the ARIMA model.

3. Data

County level data for two sectors of the economy in Sarasota, Florida were examined. The motivation to study this county came from its location on the Gulf coast, and unfortunately its place in the heart of the two worst blooms in recent history. The motivation to study these sectors came from previous papers, (Baumann et al., 2008) and the fact that tourism is a driving force and factor in the health of the county's economy (Larkin and Adams, 2007; Morgan et al., 2009). Following Larkin and Adams (2007), the two sectors examined were the restaurant and hotel/lodging sector, highly correlated with tourist activity.

Daily red tide samples were collected from January 2002 to November 2018, using the predictions of the University of South Florida-Florida Fish and Wildlife Commission Collaboration, and subsequent collections of water samples by NOAA, using the Harmful Algal Bloom Observation System (HABOS), publicly available online. The predictions made by the USF-FWC Collaboration impelled uptakes in sampling from NOAA in later years around expected periods of blooms, and otherwise, NOAA continued its routine sampling procedures (Florida Fish and Wildlife Conservation Commission (FWC), 2018).

Daily samples were then categorized into five levels, depending on the concentration of *karina brevis* cells per liter of water. The first, "Not-Present, or Background Concentration" accounts for those with less than 1000 cells of kb/L. No effects are anticipated from this level of bloom. The second, "Very Low", is when cell counts fall between 1000 and 10,000 kb/L. There are possible respiratory issues and minor halts in shellfish consumption at this level. The third, "Low", is for cell counts between 10,000 and 100,000 kb/L. Effects are similar to previous levels and additionally, there are possible fish kills and beach closures. The fourth, "Medium" (100,000 < kb/L < 1000,000) has similar effects as lesser levels, but the probability of fish kills and beach closures is largely increased. Lastly, level 5, "High" (kb/L > 1000,000) almost all but assures respiratory issues, beach closures, fish kills, and halts to shellfish consumption. For this paper, a day counted as having red tide if any of the beaches tested in the county resulted in a sample of "low" or higher. Then these daily results were aggregated in order to generate a monthly binary variable equal to 1 if that month had over 20 days of red tide exposure.

Taxable sales for each sector were collected from the Florida Department of Revenue during this same 202-month period. The data is publicly available and comes in gross dollars form. The data was adjusted for inflation by using the Bureau of Labor Statistics CPI to bring all taxable sales into 2002 numbers, the base year of our study. It should be noted that not every county had the same sectors of taxable sales processed, so it would not have been feasible to look at all of the counties in Florida simultaneously. This paper focused on more of a localized macroeconomic effect, and studies just Sarasota and the

Table 1
Summary Statistics (Standard Errors in Parentheses).

	Sample Mean in Sarasota	Sample Mean in Manatee	Sample Mean in Charlotte	Sample Mean in Lee	Sample Mean in 16- county Control Group
Lodging Sales	$ 23,600,000	$10,600,000	$3,890,673	$43,000,000	$26,800,000
	(9,528,945)	(5,078,941)	(2,405,553)	(21,200,000)	(46,400,000)
First Differenced 12-month growth rate in Lodging Sales	.00023	.00026	−.00153	−.00106	−.00096
	(.13143)	(.12446)	(.63243)	(.10388)	(.27863)
Restaurant Sales	$ 46,400,000	$ 32,900,000	$ 15,300,000	$ 73,300,000	$ 49,700,000
	(10,200,000)	(6,910,280)	(3,502,833)	(18,300,000)	(73,000,000)
First Differenced 12-month growth rate in Restaurant Sales	.0000069	−.00049	−.00059	−.000403	.00025
	(.05066)	(.04152)	(.06626)	(.04962)	(.09363)

surrounding counties. Table 1 presents summary statistics of the data.

4. Methodology

Multiple methods were used to find and examine sector-based effects of a harmful algal bloom. The first, an ARIMA model, mapped taxable sales in each sector for just Sarasota County. The second method took into account the sales of nearby Manatee, Charlotte, and Lee County, along with others, so as to purge out any regional trends that may have impacted sales other than red tides. In both methods, and for each sector, the model is:

$$y_{ct}^{*} = \beta_0 + \sum_{p=1}^{P} \Phi_p y_{c,t-p}^{*} + \sum_{q=0}^{Q} \Theta_q \varepsilon_{c,t-q} + \mu year_t + \lambda redtide_t + \varepsilon_t$$

where y_{ct}^{*} is taxable sales in 2002 dollars for a given sector and given county c, in time-period (month) t. P is the number of lagged values of the dependent variable, the autoregressive part of the model (AR), Q, the number of lagged values of the error term, or the moving average (MA), and ε_t is the error term. $Redtide_t$ is a dummy variable equal to 1 if the month experienced over 20 days of red tide levels above 10,000 kb cells/L (low to high abundance). There are also dummy variables for each of the sixteen years ($year_t$) to account for any macroeconomic trends over time, with the year 2002 serving as our omitted group. The variable of interest, λ, can be interpreted as the 12 month percent change in taxable sales for a sector, in a month when red tide was present, compared to the same month in other years without red tide.

First, only Sarasota County was examined. Following Baumann et al. (2012) the 12-month growth rate of each taxable sale sector was calculated. This process usually makes the data stationary, in addition to correcting for seasonality in the data (Baumann et al., 2012). Dicky-Fuller and Phillips-Perron (1988) tests were used to search for unit roots in the levels of data for each sector, in all counties. Using Sarasota County, these tests both could not reject the null hypothesis of a unit root for the 12-month growth rate. So, in order to make the data stationary, the first difference of the 12-month growth rates was taken. Both Dicky-Fuller and Phillips-Perron now rejected the existence of a unit root using the first differenced 12-month growth rates, and thus can be used as the dependent variable.

5. Results

Table 2 displays the results for the ARIMA model, using only Sarasota County. First, the Ng-Perron test was used to find an estimated number of AR lags to try in the model selection (Ng and Perron, 2001). Then, the Akaike Information Criterion was used to find the optimal number of lags for both the AR and MA dimensions so as to have the best possible model fit. Robust standard errors were calculated on the coefficients. It should be noted for all counties that were tested, that while the AR lags were continuous ranging from months 1 to 14, the MA lags were not. After much trial and error, the lowest AIC came from models with MA lags ranging from 1 to 3, and then an additional MA (12), most likely due to the seasonally lagged error terms. For Sarasota County, the optimal AR lags were 12 for the lodging sector, and 14 for the restaurant sector. The optimal number of MA lags were 1,2,3 and 12 for both sectors. For the two sectors, during months when red tide blooms were severe and persistent, we find taxable sales decreased by 15.67% in the lodging sector, and by 1.74% in the food sector, when compared to the base categories of untreated months. Both are statistically significant at the 5 percent level.

6. Discussion

For both the lodging and food and restaurant sector, the results showed losses that are smaller, but consistent in sign with that of previous studies (Morgan et al., 2009). The smaller effect can be attributed to the substitution effect amongst consumers. The previous studies that only looked at beachfront restaurants were observing businesses that in the short-run, could not react and adapt to the negative effects of red tide. They were easily substituted out by consumers who chose to go elsewhere, or simply just not go anywhere at all. Since in this study the whole county was sampled, naturally consumers who shift their preferences more inland negated the overall losses somewhat. This intuitively can explain why a more drastic decline in the lodging sector compared to the food sector is shown. A vast majority of the hotels are highly concentrated in a small distance to the shoreline, making them more vulnerable to red tide effects, whereas restaurants are more likely to be spread out within the county.

Table 2
ARIMA Results, Sarasota County.

	Lodging	Food
Red tide	−.1567***	−.0174 ***
	(.0652)	(.0084)
AR(1)	.4850 ***	−1.212 ***
	(.0665)	(.0815)
AR(2)	−.0996 ***	−.9909 ***
	(.0790)	(.1012)
AR(12)	.4662 ***	−.3557 ***
	(.0793)	(.1438)
AR(13)	–	−.4491***
		(.1566)
AR(14)	–	−.1888 **
		(.0995)
MA(1)	−2.170 ***	.2142 ***
	(.0751)	(.0466)
MA(2)	1.188 ***	−.1536 ***
	(.0780)	(.0485)
MA(3)	–	−.2177 ***
		(.0596)
MA(12)	−.0187 ***	−.8161 ***
	(.0034)	(.0747)
Log-Likelihood	254.6407	414.3192

Year dummies are included in each model but omitted for brevity. *** and ** represent statistical significance at the five and ten percent level respectively. All robust standard errors are in parentheses.

7. Multiple counties

Next, the model was used to test if the impact to the Sarasota economy during these months was in fact due to the red tide, or perhaps another macroeconomic trend that was driving the results, and thus the impact was unspecific to just Sarasota. Now introduced was a control group of 3 neighboring counties to Sarasota, Manatee, Charlotte and Lee County. This was done to test if the impacts of the bloom were isolated to Sarasota, and also to ensure that it was truly the red tide events that were causing these negative economic effects.

Since these control counties did not experience any months with 20 or more days of red tide, it was enough to replace the red tide dummy variable with a dummy variable equal to 1 when the month and year in these counties matched that of a bloom affecting Sarasota. Thus, there was now a dummy variable mimicking the months when severe blooms occurred in Sarasota. This in essence created a placebo effect, in that if it was not believe the effects in Sarasota were due to red tide, similar declines should have been seen in neighboring counties during the same time period, due to whatever other macroeconomic effect was driving the results. Each of these counties was tested individually, similar to the ARIMA method used testing just Sarasota. For the Manatee County lodging sector, the optimal number of lags were 1 through 12 for the AR term, and 1, 2 and 12 for the MA term, whereas the food and restaurant sector has AR lags of 1 through 14, and MA lags of 1,2,3 and 12. The Charlotte County food and restaurant sector has the same number of lags for both AR and MA as the Manatee model. However, the lodging sector actually had a much different number of optimal lags; the AR

Table 3
ARIMA Results, Manatee, Charlotte and Lee County.

	Manatee		Charlotte		Lee	
	Lodging	Food	Lodging	Food	Lodging	Food
Red tide	−.0252	−.0081	−.0096	.0065	−.0212	−.0052
	(.0193)	(.0082)	(.0535)	(.0135)	(.0296)	(.0142)
AR(1)	−1.120***	−1.248***	−.9403***	−.8057***	−.7882***	−.9636***
	(.1297)	(.0914)	(.1552)	(.1290)	(.0878)	(.2376)
AR(2)	−1.626***	−1.051***	−1.287***	−.8216***	−.4879***	−.8161***
	(.1716)	(.1307)	(.2284)	(.1526)	(.1217)	(.2840)
AR(12)	−.1386	−.6730***	–	−.4214***	−.1520***	−.6182***
	(.0881)	(.1121)		(.1684)	(.0718)	(.1638)
AR(13)	–	−.7786***	–	−.1939	–	−.5847***
		(.0966)		(.1888)		(.2006)
AR(14)	–	−.5722***	–	−.1126	–	−.4112***
		(.0717)		(.1141)		(.1618)
MA(1)	.2372***	.3812***	–	−.1712**	−.1421	−.0454
	(.1090)	(.1000)		(.0951)	(.0907)	(.2287)
MA(2)	.7080***	−.2363***	–	−.0377	−.2550***	−.2193***
	(.0835)	(.0411)		(.1129)	(.0780)	(.0840)
MA(3)	–	.6399***	–	−.1652	–	−.4765
		(.0918)		(.1123)		(.2965)
MA(12)	−.4052***	−.4394***	–	−.7497***	−1.000***	−.4923
	(.1276)	(.1241)		(.0866)	(.0430)	(.3455)
Log-Likelihood	220.9665	444.2135	−105.7767	349.0353	252.3108	394.6324

Year dummies are included in each model but omitted for brevity. *** and ** represent statistical significance at the five and ten percent level respectively. All robust standard errors are in parentheses.

term was optimal at 1 through 9, and the best model fit with the lowest AIC was produced with no MA lags at all. For Lee County, the models were exactly the same as Manatee County for both the lodging, and food and restaurant sector.

Table 3 shows no significant effects, for all three counties and for each sector. Although the results on the red tide variable were mostly correct in sign, they were not nearly statistically significant enough to be valid, even at the 10% level. An explanation for these results could be the localized responses to the issues caused by red tide. Harmful blooms in Sarasota as shown earlier, cause beach closures, seafood restrictions, and respiratory issues. However, actions taken in Sarasota need not necessitate similar actions in the surrounding counties. Beaches in nearby counties could be safe for use as could seafood consumption, and the air quality could be free of airborne brevetoxins. This could explain the lack of statistically significant decreases in these sectors for the nearby counties. It can then be concluded that the results suggest the effects of the bloom were localized to Sarasota, and red tide was in fact to blame for the decrease in taxable sales.

More formally, the combined Sarasota and control region were tested simultaneously, to again test if the results were just significant to Sarasota, or if there was a macroeconomic trend in the region affecting sales. Now that there were multiple counties, the data became a time-series cross-section. Following Baumann et al. (2012), this study used the technique developed by Arellano and Bond (1991), known as the differenced Generalized Method of Moments (GMM) to produce consistent estimates with this new dataset. The usefulness of this test and the problem of consistent estimators when dealing with this type of dataset can be found in Bond (2002) and Roodman (2006).

Additionally, Holtz-Eakin et al. (1988) note that each instrument produces a moment condition to estimate the parameters. Due to the large time period under study, the 16 years provided a plethora of instruments. However, this also necessitated a larger number of groups (counties), so that the number of instruments (number of lags) was greater than or equal to the number of groups (Roodman, 2006). In addition to Sarasota, 16 nearby counties were taken to add as a control group for the overall time-series cross-section data: Charlotte, Citrus, Collier, Miami-Dade, Desoto, Dixie, Hardy, Hendry, Hernando, Hillsborough, Lee, Levy, Manatee, Monroe, Pinellas and Polk County. Any localized macroeconomic event that occurred during the time of the red tide blooms would also be captured by these nearby counties as well and subsequently shown in the Arellano-Bond model. Introduced again was a similar dummy variable to the one that was used when the three neighboring counties were tested independently. The model replaced red tide with a dummy variable equal to 1 during the month and year that matches the dates of the blooms in Sarasota, since none of the other 16 counties experienced any months with over 20 days of red tide from 2002 to 2018.

The overidentification test introduced by Hansen (1982) was implemented to determine the number of higher-order lags of the dependent variable y_{it} to be used as instruments. A finite-sample correction shown in Windmeijer (2005) was used to correct the downward bias on the standard errors that the Arellano and Bond technique was found to produce since its first introduction. Unit roots were tested for in the data before making adjustments to make the data stationary. Unit root tests for the time-series cross-section (Levin et al., 2002 and Im et al., 2003) did not reject the existence of a unit root using the 12-month growth rate for each sector when using the combined county data for both food and lodging. However, these same tests rejected the null hypothesis of a unit root using the first differenced 12-month growth rate for each sector, thus the first differenced 12-month growth rate was used again.

Table 4 presents the results for the time-series cross-section data, using the Arellano and Bond method. What can be seen is that the results, although negatively signed, are no longer statistically significant, even at the 10% level. The results again suggest that during the months

Table 4
Arellano and Bond Model Results, Combined County Results.

	Lodging	Food
Red tide	−.0302 (.1048)	−.0629 (.0810)
Instruments (no. of lags of dependent variable)	8,9,10,11,12	6,7,8,9
Hansen test for Over-Identification	$\chi^2 = 1.22$ p = .543	$\chi^2 = 1.65$ p = .199

Year dummies are included in each model but omitted for brevity. *** and ** represent statistical significance at the five and ten percent level respectively. All robust standard errors are in parentheses.

that red tide was present in Sarasota, the nearby counties were not affected, and thus the economic impact due to the harmful blooms was localized to where it took place in Sarasota.

8. Conclusion

Red tide blooms have wreaked havoc on Sarasota County, and there have been significant economic losses during persistent events. We find lodging sector sales decrease by over 15%, and restaurant sales decrease by 1.74% in effected months. The smaller magnitudes of losses compared to previous studies might better reveal the true impact of the blooms, as substitution effects are an intuitive explanation. Additionally, as more blooms have occurred since previous literature was produced, we had more severe red tide events to categorize as "mega-events" and more rigorously test for effects using an ARIMA model. The results also suggest that the impacts are much more localized to the counties where the blooms take place. However, as blooms travel up and down the Gulf, this does not mean all other counties are safe. The impacts are severe, and very troublesome for a tourism reliant state such as Florida. As these blooms become more severe and persistent, mitigation of these blooms must become paramount for all impacted, or else costs, damages, and losses will only increase.

Declaration of Competing Interest

I wrote this paper with the intent to give new insight into the economic effects of these blooms. After much studying, I thought that I could introduce a new model into the literature. Given the severe bloom in 2018, I thought the need for this sort of information would grow, and I wanted to study it. I think this paper does two things: It affirms the studies by Larkin et al. and all others at UF that already took place, while at the same time incorporates more economic intuition. Studying the whole county allows for more variation and substitution effects, so the losses we see in this paper are not as severe as those few firms right on the shoreline.

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