The Economic Impacts of Tropical Cyclones on a Mature Destination, Florida, USA

Christina E. Brown[1,2], Sergio Alvarez[1,2], Naveen Eluru[3], Arthur Huang[1]

Abstract:

Climatic hazards such as tropical cyclones pose multi-faceted threats to coastal tourism, inflicting physical damage to infrastructure, causing business interruption, and requiring the evacuation of tourists, not to mention the ensuing damage to the destination's image. Using the State of Florida, USA, as a case study, this research integrates GIS-based tropical cyclone wind swath data with industry-level monthly sales data in a cross-county panel to explore the differential impacts of these extreme weather events among inland and coastal destinations. This study uses secondary data collected by from the state of Florida and the US federal government to estimate revenue losses to 6 sectors in Florida's tourism economy due to tropical cyclones between 2008 and 2018. Based on the pooled sample of all counties, mean per county losses were estimated to be approximately $10 million during the month of the storm, $12 million in the first month post-storm, and $7 million in the second month post-storm. Coastal counties had mean estimated losses of approximately $12.5 million in the month of the storm and persistent effects for the following 2 months. Inland counties had estimated losses of approximately $7.5 million in the month of the storm and a positive recovery effect in the fourth ($1.6 million) and fifth ($2.7 million) months post-storm. These results suggest that Florida's coastal counties are most impacted by tropical cyclones in terms of tourism-related losses.

Keywords: tropical cyclone, panel data model, coastal tourism, county level analysis

[1] Rosen College of Hospitality Management, University of Central Florida
[2] National Center for Integrated Coastal Research, University of Central Florida
[3] Department of Civil, Environmental, and Construction Engineering, University of Central Florida

The Economic Impacts of Tropical Cyclones on a Mature Destination, Florida, USA

1. Introduction

Coastal resources are critical for tourism development and local citizens' livelihoods. In the United States, 2.4 million people are employed by ocean-based tourism and recreational industries (NOAA, 2020). The state of Florida is a world-renowned destination known for its mild winter weather, beaches, and attractions ecosystem (Atzori et al., 2018). Data from Visit Florida (2019) show that in 2018, Florida received approximately 124.7 million out-of-state visitors, a 5.3% increase from 2017. Domestic visitors comprised 88.5% of total visitors in Florida in 2018, an increase of 6% over the previous year. In total, visitor spending directly and indirectly supports approximately 1.5 million jobs in Florida, with coastal tourism playing a crucial role; yet this critical component of the state's economy is vulnerable to hazards such as tropical cyclones.

At a global scale, coastal areas are home to 40% of the world's people and receive nearly 50% of international inbound tourism (United Nations, 2017). The reasons coastal areas are sought after by tourists include but are not limited to: sun, sand, and sea (SSS). However, the natural amenities that are the foundation of SSS tourism are under threat due to climate change. For example, a rise in mean global temperatures of just 1.5 °C above pre-industrial levels is expected to result in temperature-dependent changes to tourist comfort and to changes in the length of tourism operating seasons (Hoegh-Guldberg et al., 2018). Some climate-dependent tourism activities, including visits to U.S. national parks (Monahan et al., 2016) and the ski tourism industry (Scott et al., 2020), are already being influenced by climate change. Similarly, it is expected that sea levels will rise throughout the globe, putting coastal tourism assets and attractions—including dozens of UNESCO World Heritage Sites (Marzeion and Levermann, 2014) and nearly one-third of resorts in the Caribbean (Scott et al., 2012; Scott and Verkoeyen, 2017)—at risk of flooding. As global sea levels rise, it is also expected that beach erosion will accelerate (Leatherman et al., 2000), thus eroding the main attraction of coastal destinations. Coupled with sea level rise-driven coastal recession, ambient trends in shoreline dynamics could result in the loss of nearly half of the world's sandy beaches by 2100 (Vousdoukas et al. 2020).

Recent studies suggest that the intensity, frequency, and duration of North Atlantic hurricanes have been increasing since the early 1980s, and hurricane intensity and rainfall are projected to increase as the climate continues to warm (Hoegh-Guldberg et al., 2018; IPCC, 2019; Knutson et al., 2013). While tropical cyclone wind fields typically range from tens to hundreds of kilometers in diameter, Hsu et al. (1998) found the average radius of maximum wind, or the distance between a storm's center and its strongest winds, is 47km (29mi). Climate change, combined with coastal development, is expected to increase hurricane damage and worsen tropical cyclone-induced coastal flooding (Dinan, 2017; Marsooli et al., 2019), with "supercharged" storms like 2017's Hurricane Harvey heightening the risk of major damage (Trenberth et al., 2018). While there is spatial variation in hurricane risk across different regions of the United States, Pant et al. (2019) found that climate-dependent future hurricane risk is higher than present risk for all locations. Klotsback et al. (2018) note that regardless of any future increases in tropical cyclone frequency or intensity, hurricane-related damage will increase due to growth in coastal population and wealth. Additionally, as the climate increases to warm over time, hurricanes' damaging impacts will be felt farther inland (Li et al., 2020).

Climatic hazards such as tropical cyclones pose a multi-faceted threat to coastal tourism. Like other natural disasters, tropical cyclones impact the destination by inflicting physical damage to infrastructure, temporarily closing tourism operations, and requiring the evacuation of tourists, not to mention the ensuing damage to the destination's image (Bigano et al., 2005; Forster et al., 2012; Gössling and Hall, 2006). With their destructive energy, tropical cyclones also compound on the impacts of sea level rise as their storm surge causes widespread coastal flooding accompanied by rapid and drastic changes in beach morphology (Cuttler et al., 2018). Though a tropical cyclone's winds, rain, and storm surge impact on a specific area is short-term, the economic impacts on both local and regional scales last much longer (Grinsted et al., 2019). For instance, business closures in the aftermath of these cyclones may last for weeks or even months, while disruptions to the electric grid and critical supply chains such as fuel and food may last for days or weeks (Ewing, et al., 2014). Butler (2012) cautions that revolutionary, sudden changes that bring about the destruction of existing features, pose a significant threat to the endurance of mature destinations. Climatic hazards such as tropical cyclones, which bring the destructive forces of nature to the destination with increasing frequency and intensity, are precisely the kind of revolutionary change that pose a clear and present threat to mature coastal destinations.

It can be argued that Florida is the quintessential mature destination envisioned by Butler's (1980) tourist area life cycle model. Florida's *exploration stage* dates back to the 1820s with seaside destinations St. Augustine, Pensacola, and Key West emerging as refuges from tuberculosis and other respiratory ailments. By the 1850s, Florida's navigable rivers became steamboat cruise routes for nature enthusiasts, including sportsmen shooting alligators. During this exploration period, Florida was mostly unpopulated, difficult to reach, and seen as America's last frontier. The *involvement stage* began after the US civil war and lasted into the early 20th century, with a growing number of spas and lodgings along the coast drawing increasing numbers of tourists. During this period, oil and railroad tycoons Henry Flagler and Henry Plant played a key role in the development of Florida as a tourist destination by building the first tourism infrastructure including resort-style hotels and a system of railroads that extended south to Key West. At this time, tourism became deeply engrained in the state's economy, with settlements built to house construction crews for hotels and hospitality workers becoming cities like Miami and West Palm Beach. The involvement stage culminated in the 1920s, when catapulted by democratization of tourism in the US following the advent of Ford's Model-T automobile, Florida reached its *development stage*. The state's road system was improved with many of the old railroads paved into roads, opening the door for larger numbers of tourists that made attractions such as zoos and alligator farms profitable, and the first theme parks were built. Similarly, affordable lodgings and campgrounds proliferated throughout coastal and inland areas of the state (Revels, 2011).

Florida was entering a *consolidation stage* in the mid-1920's, but two deadly category 4 hurricanes, one in 1926 making landfall in Miami and another in 1928 making landfall in West Palm Beach, deeply impacted Florida's tourism and precipitated the first *stagnation stage*. Besides bringing mass destruction to Miami and West Palm Beach, which had become major destinations within Florida, images of thousands of bloated bodies and headlines stating “Florida Destroyed!” proliferated across the US (Revels, 2011). The impacts of back-to-back hurricanes combined with the Great Depression and World War II to send Florida into a *decline stage*.

Florida’s first *rejuvenation stage* was induced by America’s post-war prosperity, a period when Florida’s image of year-round fun in the sun, amusement parks and attractions, became established. A second *rejuvenation stage* can be said to have taken place in the 1970s with the construction of Walt Disney World and the ensuing development of the theme park cluster in central Florida (Revels 2011). While Butler (1980) noted Miami Beach as entering a *decline stage* in the 1980s, tourism has continued to grow in Florida during the 21st century, and the year prior to the COVID-19 pandemic received roughly six times as many visitors as it had permanent residents.

Today, Florida is a diverse tourism ecosystem where beaches, theme parks, and shopping malls are complemented by less trodden attractions such as freshwater springs and the Everglades. Tourism is deeply engrained in the state’s identity, and, indeed, “Florida has been a trusted destination for generations, with decades of visitation growth as proof” (Visit Florida, 2018). Like other tourism destinations across the globe, Florida has also been deeply impacted by the COVID-19 pandemic (Larson and McDonald, 2020), which is likely to be the harbinger of a new *consolidation* and *decline* stage. Butler (2012) argues that to avoid decline into obsolescence, destinations must be managed effectively and appropriately, using a combination of innovation with new and fashionable tourism products and infrastructure, as well as conservation of the natural and cultural resources that attract tourists in the first place. In a sense, Florida’s continued success as a tourism destination depends on the active involvement of local and state governments and the private sector in the management of tourism and the conservation of natural resources.

While it is widely acknowledged that tropical cyclones are bad for tourism and the economy, there is less understanding of their specific impacts on industries. For example, damage assessments in the wake of cyclones in the US focus on damage to structures and other types of property, but rarely consider any changes to business activity or revenue. There is little understanding of both short-term and long-term economic impacts. Further, the path of recovery for the tourism industry in the wake of tropical cyclones is not well understood. This paper aims to shed light on these issues by measuring the impact of tropical cyclones on the tourism economy for a mature destination using the state of Florida, USA, relying on an interdisciplinary approach that brings in data compiled by the atmospheric sciences to estimate tropical cyclone impacts and reveal the path of post-cyclone recovery. We integrate GIS-based tropical cyclone wind swath data with monthly, county-level sales data by industry to estimate the short and long-term impacts of tropical cyclones on the tourism economy using a panel regression model that controls for trend and seasonality to identify the short and long-term impacts of tropical cyclones on the tourism sector. Our approach goes beyond property damage as a measure of cyclone impacts and uses the losses of operating revenue as an index for the impact of cyclones on economic activities. Furthermore, spatial analysis and time-series analysis are combined to gain new insight on the impact of tropical cyclones and the path of post-cyclone recovery. Finally, our quantitative analysis explores the differential impacts between inland destinations and coastal destinations with waterfront areas, and investigates the recovery period of the tourism industry from historical tropical cyclones.

The rest of the paper is structured as follows. Section 2 provides an overview of the literature on the impacts of tropical cyclones on tourism. Section 3 describes the methods, including study area, data, and econometric specification. Section 4 summarizes the result, and section 5 provides a discussion of the study’s implications. Section 6 concludes this paper.

2. Tropical Cyclones and their Multi-Faceted Impacts on Tourism

There has been a growing interest in investigating the exposure of tourism activities to tropical cyclones. Recent studies have shown that tropical cyclones result in reduced tourist arrivals and spending at destinations (Bang Vu et al., 2017; Granvorka et al., 2013; Rosselló et al., 2020). However, Prideaux et al. (2008) found that these negative impacts tend to be short-term and vary among different tourist segments. Becken (2010) argued that weather not only plays an important role in tourists' decisions on activities at a destination, but also influences the successful operation of tourism businesses. With respect to tourists' response to hurricane warnings in Florida, Cahyanto et al. (2016) found that tourists with greater connectedness to the destination are more likely to have knowledge of the possibility of hurricane threats and issuances of evacuation notices. In terms of response to increased risk of hurricanes due to climate change, Forster et al. (2012) found that tourists to the Caribbean are significantly less likely to vacation where they perceive an increased risk of hurricanes, with 40% of tourists to Anguilla considering hurricanes in their decision-making process. In addition, tourism operators have identified clean-up, rebuilding of infrastructure, business assistance, and communications and media engagement as critical aspects during disaster recovery (Becken et al., 2013).

In a global analysis of the impact of hazards on tourism demand, Rosselló et al. (2020) found that storms rank first in terms of the economic costs of disasters, comprising 38% of the total global economic losses during the period 1995–2013. Furthermore, their findings indicate that while only 16.8% of storms take place in the Americas, the cost is disproportionately high (66.1%) with respect to other regions. Chandler (2004) took a three-month snapshot view of the effects of three hurricanes and extensive flooding on North Carolina's lodging industry, estimating total direct revenue losses of $3.8 million across the coastal and heartland regions of the state, not accounting for physical damage to properties and other losses. Fitchett et al. (2012) note that lodgers in South Africa following Tropical Storm Dando incurred short, medium, and long-term losses, with the predominant source of losses in the medium-term incurred due to business interruption. Referencing the aftermath of Hurricane Sandy, Choi et al. (2019) suggest that dynamic pricing could mitigate some revenue losses and their study "supports the importance of the lodging industry to the economies of states affected by a natural disaster."

Historic accounts indicate that tourism operators, such as hotels and fishing and diving charters, suffer economic losses due to tropical cyclones (Abbot, 2019; Stapleton, 2019). Operators reported losses in bookings following Hurricane Irma in September 2017, but by December 2017 occupancy had returned to normal (Fox, 2018). While 2019's Hurricane Dorian did not make landfall in Florida, operators reported reduced tourism revenue over the Labor Day weekend due to business interruption and a slowdown in bookings through November of that year (Abbot, 2019).

A number of studies have examined the impact of natural disasters on economies from a macroeconomic perspective. Yang (2008) examined the impact of hurricanes on international financial flows to developing countries. In a theoretical analysis, McDermott et al. (2014) argued that, given access to credit, increased investment will fully compensate for any losses to the capital stock due to an extreme event such as a natural disaster in a high-income economy; and yet, a disaster will reduce output in the short-term as well as reducing the growth rate of the economy in the medium to long term in a low-income economy. An empirical analysis by Skidmore and Toya (2002) used cross-country panel data to demonstrate that climatic disasters such as cyclones are positively correlated with economic growth, while geologic disasters on the other hand are negatively correlated with growth. Schumacher and Strobl (2011) also employed a cross-country panel dataset, investigating the relationship between losses, exposure to hazard, and stages of development. Klomp (2016) and Toya and Skidmore (2007) explored the relationship between natural disasters and economic development through factors such as nighttime light intensity and individuals' educational attainment and openness.

Studies on the effects of disaster vulnerability and resilience have found that community resilience is a strong factor in how natural disasters affect hospitality industry employment (Sydnor-Bousso et al., 2011), and bigger tourism-based regional economies prior to natural disasters tend to have lower disaster losses than those with smaller economies (Kim and Marcouiller, 2015). Burrus et al. (2002) focused on regional business interruption from low-intensity hurricanes, reporting that while per-strike losses may be small, the high frequency of hurricanes and tropical storms produces a cumulative economic impact equivalent to a high-intensity hurricane strike. Ewing et al. (2010) examine regional state-level economic responses to Hurricane Katrina in Louisiana, suggesting that composite indices provide a more comprehensive estimate of changes in the regional economy than single indices such as GDP.

However, the regional impacts of tropical cyclones on the economy remain understudied, with most damage assessments focusing mostly on damage to property (Pielke and Landsea, 1998). Thus, the impacts on broader revenue streams in vulnerable sectors such as tourism are largely unknown. There is limited understanding about how costs and losses incurred as a result of tropical cyclones are distributed through time, or how long economic recoveries generally take. Information on the true costs of cyclones, as well as their short-term and long-term impacts, is essential for polices such as mitigation investments and sustainability planning. Therefore, this study aims to measure short and medium-term impacts of tropical cyclones on the tourism economy in a mature destination from the month of a tropical cyclone's occurrence up to six months post-storm.

The use of county-level monthly sales data from the state of Florida provides a complete and aggregate view of all tourism-related expenses in the state across time, both in areas that were impacted by tropical cyclones, and in areas that were not. Therefore, the use of this secondary dataset allows empirical estimation of the true impacts of tropical cyclones on tourism-related sales, providing a big picture view at the county and state level that does not rely on extrapolation of results from a small sample. In contrast, studies that rely on small samples from surveys (e.g. Fitchett et al. 2016) can provide a great deal more detail about the individual tourism operators that were surveyed (including qualitative data), but extrapolation of results to the entire tourism economy of an impacted region is problematic unless the sample can be guaranteed to be representative of all tourism businesses in the region, which requires sampling across all tourism-related businesses of all sizes, and a high response rate, which can be challenging to achieve.

3. Methods

3.1. Study Area

Our study area includes 67 counties in the state of Florida, with 35 coastal counties (where any portion of the state includes coastline) and 32 inland counties. Tourism-related spending in Florida displays a marked seasonality, particularly in coastal counties. The high season coincides with the Northern

Hemisphere winter, a time when Florida’s sub-tropical warm temperatures offer a strong contrast to the rest of the US. Florida’s high tourism season begins in January as ‘snow-birds’ (people who over-winter in Florida) begin their annual migration into Florida. The peak of the tourism season occurs in April, when educational institutions have their ‘spring break.’ As the summer heat descends on the Northern hemisphere, Florida’s low tourism season begins, with the lowest spending occurring in the months of September and October (Figure 1a). Besides the annual seasonality observed, there has been steady growth of tourism-related sales over time following the Great Recession (Figure 1b). In addition, every one of Florida's coastal counties was impacted by at least one tropical cyclone during the study period, which ranges between 2009 and 2018 (Figure 2). As evidenced by Figure 2, some storms’ tropical storm force winds affect nearly the entire state (e.g. Irma, 2017), while others only portions of several counties (e.g. Bonnie, 2010). Florida’s Southeastern coastline is particularly susceptible to landfalling hurricanes, followed by the panhandle area in Northwest, while areas around Tampa, Jacksonville, and the Big Bend are less at risk of a direct cyclone strike. However, even if a storm makes landfall elsewhere in Florida or not in Florida at all, weather effects can cover hundreds of miles (Florida Climate Center, 2020).

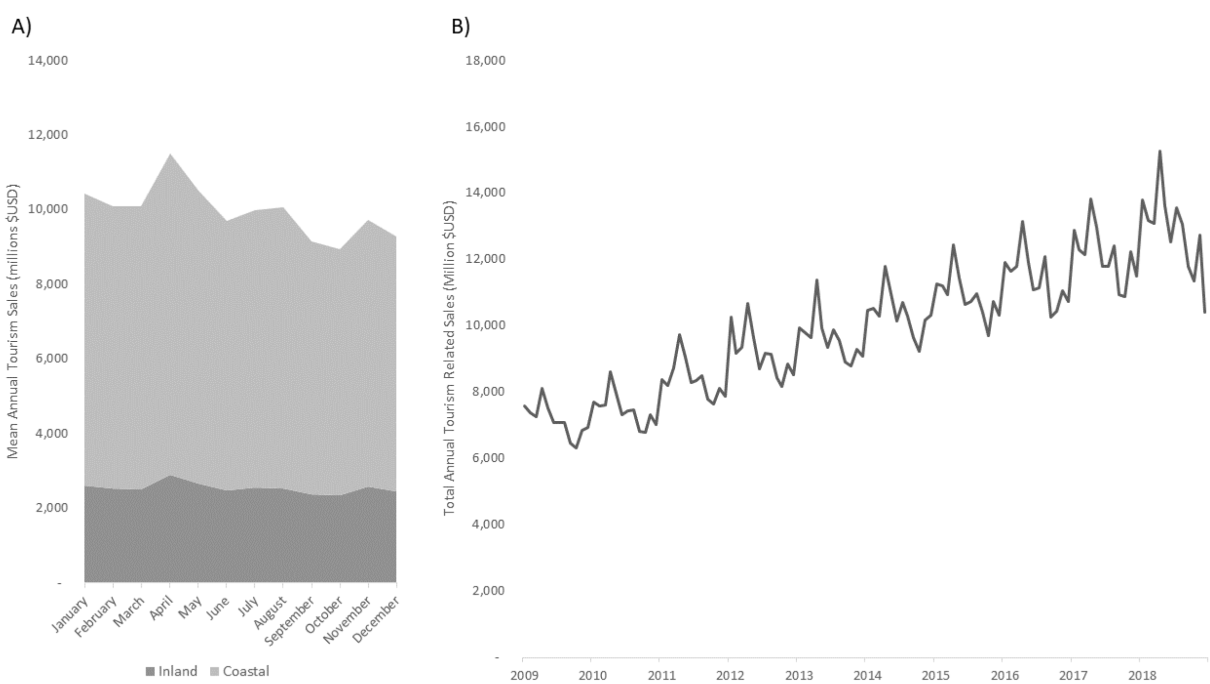

Figure 1. Seasonality and trends in Florida's tourism economy. Panel A shows annual statewide tourism related sales, averaged across the years 2009 to 2018. Panel B shows total statewide monthly tourism related sales between 2009 and 2018 (Data Source: Florida Department of Revenue).

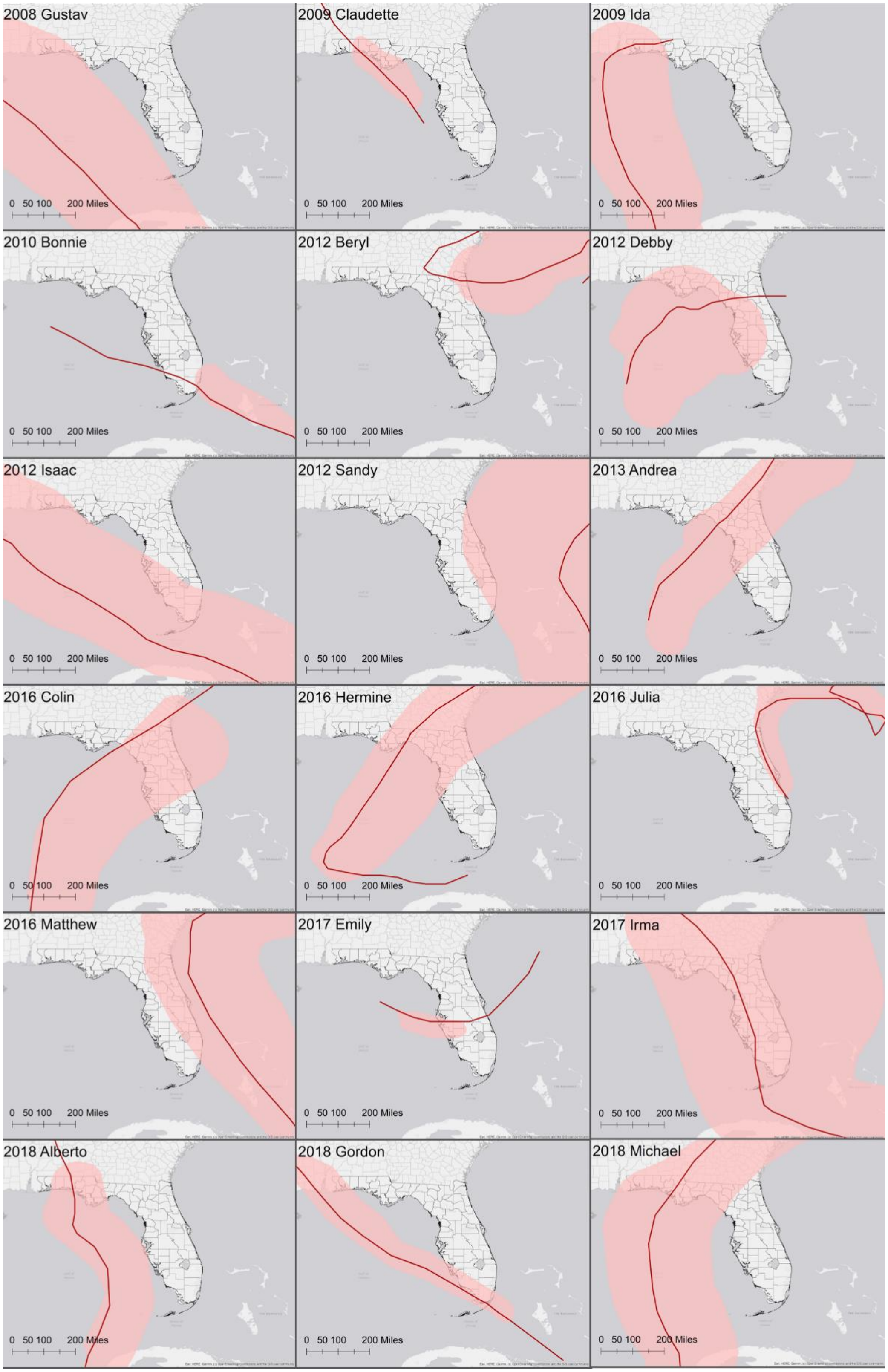

Figure 2. Tracks and tropical storm force wind swaths for the 18 cyclones analyzed in the study (Data Source: NOAA).

The Atlantic hurricane season is between June 1 and November 30 (Saunders et al., 2005). While tropical cyclones may occur outside of the season, the timeframe encompasses over 97% of tropical cyclone activity (National Hurricane Center, 2020). The peak of hurricane season in the Atlantic basin is from August through October, with 78% of tropical storm days, 87% of minor hurricane (Saffir-Simpson Scale categories 1 and 2) days, and 96% of major hurricane (Saffir-Simpson Scale categories 3, 4, and 5) days occurring during this period (Landsea, 1993).

While the threat of tropical cyclones is an annual concern for destinations along the eastern coast of the U.S. and the Gulf of Mexico, Florida is particularly vulnerable due to its location between the Gulf and Atlantic Ocean (Pinelli et al., 2011). Historically, approximately 40% of landfalling hurricanes in the U.S. have struck Florida, with a total of 120 hurricane strikes between 1851 and 2019 and 37 of these hurricanes classified as major (Hurricane Research Division, 2019).

3.2. Data

The study uses a monthly panel of county-level gross sales data (2008-2018) compiled and published by the Florida Department of Revenue covering six industries in Florida's tourism economy: food and beverage stores; eating and drinking places (not restaurants); restaurants, lunchrooms, catering services; drinking places (alcoholic beverages served on premises); hotel/motel accommodations, rooming houses, camps, and other lodging places; and rental of tangible personal property.

A tropical cyclone is a low pressure system that develops over tropical waters, characterized by high winds and heavy rain. Once the surface winds have reached a maximum sustained speed of 39 mph (63 km/h), it is classified as a tropical storm. At 74 mph (119 km/h) or greater sustained maximum wind speed, it is classified as a hurricane, at which point it is rated on the Saffir-Simpson hurricane wind scale as category 1 through 5 (Schott et al., 2019). A variety of identification strategies for tropical cyclones were considered for this analysis, from categorical variables that indicate hurricane intensity, to a binary indicator of the occurrence of any tropical cyclone (i.e. tropical storm or any category hurricane) in a particular country during a specific month. The indicators were constructed using a Geographic Information System by intersecting tropical cyclone wind swaths (National Hurricane Center, 2019) with the state of Florida and identifying which of Florida's 67 counties were affected by sustained tropical storm force winds. The historical tropical cyclones data collected from NOAA include18 tropical cyclones in Florida between 2008 and 2018 ranging in strength from tropical storms to Category 5 hurricanes (Table 1 and Figure 2).

Table 1. Tropical cyclones whose wind fields intersected Florida and maximum category strength (2008-2018).

Year	**Storm (Maximum Category Strength)**
2008	Gustav (Cat. 4)
2009	Claudette (Tropical storm), Ida (Cat. 2)
2010	Bonnie (Tropical storm)
2011	*None*
2012	Beryl (Tropical storm), Debby (Tropical storm), Isaac (Cat. 1), Sandy (Cat. 3)
2013	Andrea (Tropical storm)
2014	*None*
2015	*None*
2016	Colin (Tropical storm), Hermine (Cat. 1), Julia (Tropical storm), Matthew (Cat. 5)
2017	Emily (Tropical storm), Irma (Cat. 5)
2018	Alberto (Tropical storm), Gordon (Tropical storm), Michael (Cat. 5)

Compared with many prior studies that use aggregated data at an annual or national level (e.g. Schumacher and Strobl, 2011; Skidmore and Toya, 2002), this study uses the monthly and county level data to analyze the impacts of tropical cyclones at a finer granularity. This finer granularity can be exploited to examine critical questions about the timing and duration of the impacts of tropical cyclones on the tourism economy. In addition, this granularity also allows comparison of the differential impacts of tropical cyclones on waterfront destinations, as compared to inland tourism economies that are sheltered from the most dangerous impacts of cyclones—namely storm surge driven flooding.

A challenge inherent in this analysis is that some portions of a county may receive tropical storm winds, while another part receives hurricane force winds or stronger. To address these challenges, the indicator (labeled TC_{it}) takes a value of 1 during the month (t) in which any tropical cyclone wind field impacted each county (i), and a 0 in all other months. That is, if any portion of a county encountered a storm's wind field of at least tropical storm-force winds, that county is considered "impacted" and registers a value of 1 during the month in which the impact occurred. Furthermore, gross sales were corrected for inflation using the CPI (and converted to million $USD for ease of interpretation). Florida's state level monthly unemployment rate was included as a control for macroeconomic factors.

Lagged tropical cyclone indicators were also introduced to explore medium and long-term impacts on the tourism economy. Lags were assigned on a monthly basis and ranged from one to six months after each cyclone. Additionally, the sample was split by using a coastal indicator that takes a value of 1 for coastal counties (bordering either the Atlantic Ocean or the Gulf of Mexico). The coastal indicator takes a value of 0 for inland counties.

Several approaches to consider monthly lags were applied in order to evaluate impacts on a longer-term basis than simply the month in which tropical cyclones impacted Florida. Initially, an 18-month lag model was tested, followed by scaling down to 12-month, 9-month, and 6-month models. Specifications incorporating the various monthly lags yielded similar results to the final model specification with a 6-month lag. A major issue with the models incorporating longer time lags (9-month, 12-month, and 18-month) is that they have the potential for overlapping with the following year's hurricane season. Thus a model using a 6-month lag was selected. Results from the 9-month, 12-month, and 18-month lag models are available upon request.

3.3. Econometric models

Various model specifications were tested to determine the best model fit for each of the two subsamples (coastal vs. inland counties) and the pooled sample of all counties: a county-fixed effects model, a county- and time-fixed effects model, and a random effects model. In all models, county is coded as a categorical indicator, and in the fixed effects models unobserved variations across counties are controlled for. The county-fixed effects model is represented as:

$$Tourism_{it} = \beta_0 + \beta_1 \sum_{m=0}^{m=6} TC_{i,t-m} + \beta_2 FLUnemp_t + \gamma_i + u_{it} \quad [1]$$

Where the dependent variable $Tourism_{it}$ is gross sales in million $US aggregated across the six aforementioned tourism economy sectors for county *i* in month *t*; $TC_{i,t-m}$ is a binary indicator of the occurrence of a tropical cyclone in county *i* at month time-step lag $t - m$; $FLUnemp_t$ is the statewide unemployment rate in month *t*; γ_i is county fixed effects, and u_{it} is a normally distributed error term, independent across the observations. Finally, β_0, β_1, and β_2 are parameters to be estimated. The county- and time-fixed effects model can be written as:

$$Tourism_{it} = \beta_0 + \beta_1 \sum_{m=0}^{m=6} TC_{i,t-m} + \beta_2 FLUnemp_t + \gamma_i + \theta_t + u_{it} \qquad [2]$$

All variables are the same as in Equation [1] above, save for the addition of θ_t which represents monthly time-fixed effects. The random effects model is specified as:

$$Tourism_{it} = \beta_0 + \beta_1 \sum_{m=0}^{m=6} TC_{i,t-m} + \beta_2 FLUnemp_t + \omega_i + \varepsilon_{it}\ , \qquad [3]$$

where ω_i represents random heterogeneity specific to county *i* and ε_{it} represents independently distributed random errors for all observations.

4. Results

The three econometric models were tested separately for the inland and coastal subsamples as well as for the pooled sample of all counties. A series of tests were conducted to identify the preferred econometric models. First, we used the Durbin-Wu-Hausman (DWH) endogeneity test, which evaluates whether the unique errors are correlated with the regressors, to determine whether a random effects model was preferred over a fixed effects model (Hausman, 1978). The null hypothesis of the DWH test is that there are no systematic differences between the random effects and the fixed effects estimators, namely:

$$W = (\beta_{RE} - \beta_{FE})' \hat{\Sigma}^{-1} (\beta_{RE} - \beta_{FE}) \sim \chi^2(k) \qquad [4]$$

If W is statistically different from zero, the null hypothesis is rejected, indicating that the fixed effects estimator should be used. Second, a joint test was performed to test whether time-fixed effects were needed in the fixed effects model by checking whether the parameters associated with the indicators for all months are statistically different from zero. The null and alternative hypotheses are:

$$H_0: \theta_i = 0\ \forall \theta$$

$$H_A: \theta_i \neq 0$$

Lastly, we conducted a modified Wald test for heteroscedasticity to determine whether ‘sandwich’ estimators (i.e. heteroscedasticity-robust standard errors) were needed in the fixed effects model (Baum, 2000). The null hypothesis and alternative hypothesis are:

$$H_0: \sigma^2(i) = \sigma \ for \ i = 1, N_g$$

$$H_A: \sigma^2(i) \neq \sigma$$

Where σ is standard deviation, σ^2 is variance, and N_g is the number of counties.

4.1. Pooled Sample

Parameter estimates for the three models using the pooled sample are very similar in both magnitude and statistical significance (Table 2). The tropical cyclone indicator (TC_t), as well as the lag indicators for the 3 months following a cyclone are all significant. For the county and time fixed effects model, only the tropical cyclone indicator and lags through the second month following the storm are significant. Parameter estimates indicate smaller losses in this model compared to the county fixed effects and the random effects models. All models yield statistically significant parameter estimates for Florida's unemployment rate and constant, with expected signs.

Table 2. Pooled Sample regression results for three model specifications (TC_t indicates the happening of a tropical cyclone in month *t*).

Variable	County fixed effects	County and Time fixed effects	Random effects
TC_t	-14.5948*** (4.0842)	-10.1459** (3.8341)	-14.5932*** (3.0715)
TC_{t-1}	-13.0668*** (4.1859)	-12.23*** (4.1469)	-13.0655*** (3.0656)
TC_{t-2}	-8.5298** (3.5272)	-6.9257* (3.6128)	-8.52862*** (3.06721)
TC_{t-3}	-5.9144** (1.8512)	3.2361 (2.4979)	-5.9079* (3.1778)
TC_{t-4}	-0.0784 (1.5689)	-3.9209 (3.6487)	-0.0738 (3.2019)
TC_{t-5}	0.5237 (1.5172)	-0.8109 (2.8634)	0.5279 (3.1801)
TC_{t-6}	4.6567 (2.9363)	4.2046 (3.8551)	4.6609 (3.1905)
Florida unemployment	-10.4962*** (2.3327)	-15.5933*** (3.2442)	-10.496*** (0.2604)
Constant	225.1978*** (17.0319)	250.4045*** (21.9912)	225.1952*** (28.5108)
R-squared			
within	0.1759	0.2138	0.1759
between	0.0072	0.0024	0.0072
overall	0.0101	0.0124	0.0101

****p<0.01, **p<0.05, *p<0.10, Standard error in parenthesis*

The DWH test for the pooled sample yielded a p-value of 0.0032, rejecting the null hypothesis of a random effects model being the preferred option, and indicating that a fixed effects model should be used. A joint test to determine whether the indicators for all months are equal to 0 yielded a p-value less than 0.00, rejecting the null hypothesis and indicating that time-fixed effects are needed in this case. Finally, a modified Wald test for heteroscedasticity yielded a p-value less than 0.00, rejecting the null hypothesis of constant variance and indicating that heteroscedasticity-robust standard errors are needed.

Based on these test results, a fixed effects regression with time-fixed effects (Equation [2]) and heteroscedasticity-robust standard errors was found to be the preferred model for the pooled sample of all counties in Florida. In this preferred model, coefficient estimates for Florida's unemployment rate and the constant were significant (at the 1% level) and with expected signs. The tropical cyclone indicator (TC_t) was significant (at the 5% level) and suggested an average per county loss of $10.1 million during the month in which a tropical cyclone impacts Florida. Effects of cyclones on the tourism economy also persist for a second and third month, as shown by the statistically significant one- (at the 1% level) and two-month (at the 10% level) lag indicators, which suggests average impacts of $12.2 million and $6.9 million in the two months following a tropical cyclone.

4.2. Coastal Counties

Akin to the pooled sample of all counties, parameter estimates for the county fixed effects and the random effects models using the coastal counties subsample are similar in both magnitude and significance (Table 3). The tropical cyclone indicator, as well as the indicators for the 3 months following a cyclone are all statistically significant. For the county and time fixed effects model, only the tropical cyclone indicator and lags through the second month following the storm are significant. The estimates in the county and time fixed-effects model suggest smaller losses than in the other two models. All models' parameter estimates for Florida's unemployment rate and the constant are statistically significant with expected signs.

Table 3. Coastal sub-sample regression results for three model specifications (TC_t indicates the happening of a tropical cyclone in month *t*).

Variable	County fixed effects	County and Time fixed effects	Random effects
TC_t	-20.5129*** (6.5003)	-12.5266** (5.6536)	-20.5131*** (4.8064)
TC_{t-1}	-21.9394*** (7.3777)	-16.5855** (6.1792)	-21.9397*** (4.7997)
TC_{t-2}	-13.882** (6.0893)	-9.7018* (5.4984)	-13.8821*** (4.8026)
TC_{t-3}	-8.8646*** (3.213)	6.6026 (4.7196)	-8.8584* (4.9622)
TC_{t-4}	-1.0283 (3.1445)	-7.807 (5.5793)	-1.0247 (5.0361)
TC_{t-5}	-0.6464 (2.3565)	-2.6669 (3.9293)	-0.6447 (4.9671)
TC_{t-6}	5.8638 (4.2966)	3.8927 (4.6417)	5.8652 (4.981)
Florida unemployment	-14.9268*** (3.4283)	-22.6079*** (4.8467)	-14.9268*** (0.4006)
Constant	321.1863*** (25.0706)	361.5346*** (34.5781)	321.1851*** (44.6087)
R-squared			
within	0.2570	0.3186	0.2570
between	0.0005	0.0002	0.0005
overall	0.0165	0.0205	0.0165

****p<0.01, **p<0.05, *p<0.10, Standard error in parenthesis*

The DWH test for the pooled sample yielded a p-value of 0.0208, rejecting the null hypothesis of a random effects model being preferred, and indicating that a fixed effects model should be used. A joint test to determine whether the indicators for all months are equal to 0 yielded a p-value of 0.00, rejecting the null hypothesis and indicating that time-fixed effects are needed in this case. Finally, a modified Wald test for heteroscedasticity yielded a p-value less than 0.00, rejecting the null hypothesis of constant variance and indicating that heteroscedasticity-robust standard errors are needed.

The findings reveal that the county and time fixed effects (Equation [2]) model with heteroscedasticity-robust standard errors was preferred for the coastal counties subsample. In this model, coefficient estimates for Florida's unemployment rate and the constant were significant (at the 1% level) and with expected signs. The tropical cyclone indicator was significant (at the 5% level), suggesting an average per county loss of $12.5 million during the month the tropical cyclone occurs. Persistent effects for the 2 months following the cyclone are also evident in the coastal subsample, with average losses of $16.6 million and $9.7 million respectively in the first (at the 5% significance level) and second (at the 10% significance level) months following a storm. Notably, losses to the coastal tourism economy are larger in the month after the tropical cyclone than in the month in which the cyclone occurs. This may indicate a difference between immediate and short-term physical impacts (e.g. storm surge, business closures, cleanup, etc), and longer-term, persistent impacts to the reputation of the destination (Becken et al., 2013).

4.3. Inland Counties

In the models that use only the inland counties subsample, parameter estimates for the three model specifications are similar in magnitude, but differ in the level of statistical significance (Table 4). The tropical cyclone indicator is significant in the county fixed effects and random effects model, but not in the county and time fixed effects model. Interestingly, the county fixed effects model yields significant and positive estimates for the parameters indicating the fourth and fifth month post-storm lags. In contrast, the county and time fixed effects model yields significant and positive estimates for the third and fourth months post-storm, but not for the tropical cyclone indicator itself. In all models, Florida's unemployment rate and the constant are statistically significant and with expected signs.

Table 4. Inland sub-sample regression results for three model specifications (TC_t indicates the happening of a tropical cyclone in month *t*).

Variable	**County fixed effects**	**County and Time fixed effects**	**Random effects**
TC_t	-7.4659* (4.0897)	-7.5208 (4.7667)	-7.4606** (3.5213)
TC_{t-1}	-3.0753 (1.9508)	-4.7312 (3.2934)	-3.0707 (3.5131)
TC_{t-2}	-1.9843 (1.6637)	-1.7172 (2.7106)	-1.98 (3.5142)
TC_{t-3}	-2.0889 (1.6644)	2.0393* (1.1662)	-2.0811 (3.6439)
TC_{t-4}	1.6359** (0.7944)	3.6817* (2.1447)	1.6437 (3.6527)
TC_{t-5}	2.7871** (1.2887)	5.0216 (3.0329)	2.7652 (3.6549)
TC_{t-6}	5.0077 (3.8222)	8.2992 (5.8761)	5.0162 (3.6682)
Florida unemployment	-5.5464* (2.9101)	-7.1124* (3.7703)	-5.5459*** (0.3035)
Constant	119.1371*** (21.006)	122.0294*** (22.3282)	119.1316*** (33.2229)
R-squared			
within	0.0883	0.1042	0.0883
between	0.0119	0.1519	0.0111
overall	0.0050	0.0063	0.0050

****p<0.01, **p<0.05, *p<0.10, Standard error in parenthesis*

The DWH test for the inland county subsample yielded a p-value of 0.0402, rejecting the null hypothesis of a random effects model being the preferred option, and indicating that a fixed effects model should be used (Table 3). A joint test to determine whether the indicators for all months are equal to 0 yielded a p-value of 1.00, failing to reject the null hypothesis and indicating that time-fixed effects are not needed in this case. Finally, a modified Wald test for heteroscedasticity yielded a p-value less than 0.00, rejecting the null hypothesis of constant variance and indicating that heteroscedasticity-robust standard errors are needed.

Test results suggest that a county fixed effects model (Equation [1]) with heteroscedasticity-robust standard errors was the preferred model for the inland counties subsample. In this model, coefficients for Florida's unemployment and the constant were statistically significant (at the 10% and 1% levels, respectively) and with expected signs. The tropical cyclone indicator was significant (at the 10% level), which suggests an average per county loss of approximately $7.5 million in the month of the storm. Somewhat surprisingly, there is indication of a significant and positive bounce-back effect (at the 5% level) with increases in gross tourism related sales in the fourth and fifth months post-cyclone, respectively averaging $1.6 million and $2.7 million.

4.4. Visual Overview of Preferred Models

Visual inspection of the impact of cyclones on Florida's tourism economy in the months post-cyclone reveals interesting patterns. Taking a holistic view of all counties (Fig. 3A), there is a clear decline in gross sales by tourism-related businesses in the month of a tropical cyclone, but this reduction is much sharper for coastal counties than for inland counties (Fig. 3B and 3C). There is also an indication of a bounce-back or recovery effect, as tourism related sales seem to increase three months after a cyclone. It is important to note that this recovery effect is not statistically significant in coastal counties. In addition, the range of confidence intervals for coastal counties as well as the pooled sample is quite stable regardless of the time elapsed since a cyclone's occurrence.

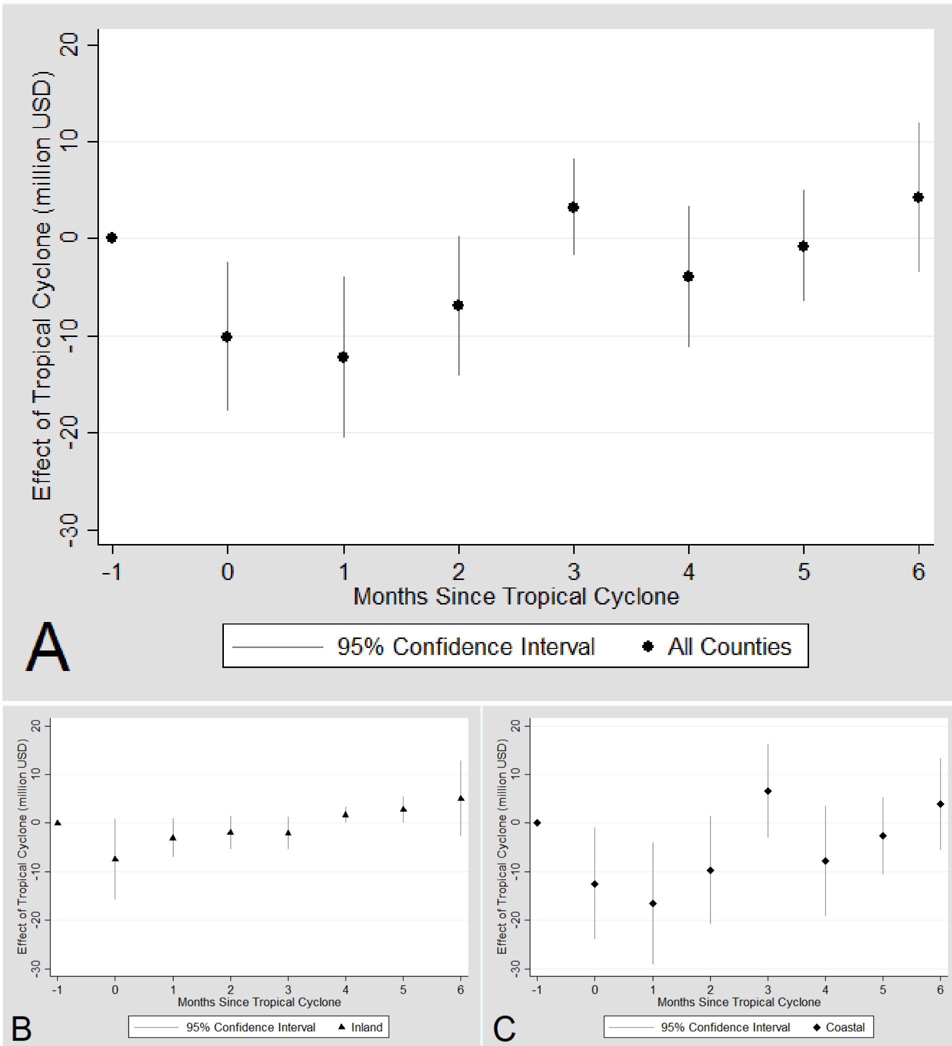

Figure 3. Mean effect of tropical cyclones on the tourism economy. Panel A shows average impacts over time for the pooled sample; panel B for the inland county subsample; and panel C for the coastal county subsample.

5. Discussion

Negative impacts or losses in revenue due to tropical cyclones occur in the short term across the board, as expected. A mean monthly loss in revenue of $10.1 million in the pooled sample of all 67 counties, combined with mean monthly losses in revenue of $12.5 million in the coastal counties subsample, suggest that coastal counties are bearing the brunt of tourism-related losses when a tropical cyclone impacts Florida. The comparatively smaller mean monthly impact of tropical cyclones for the inland counties subsample ($7.5 million) further supports that finding. It might be the case that coastal counties experience a larger disruption to tourism than inland counties due to the increased chances of mandatory evacuations from areas threatened by storm surge, which lie predominantly along the Atlantic and Gulf coastlines (FRPC, 2012). For example, during Hurricane Dorian in 2019 (outside of the study period), 26 Florida counties were placed under a state of emergency by the governor on August 28 (Executive Order Number 19-189, 2019) and the following day the order was expanded to all counties in the state (Executive Order Number 19-190, 2019). While the storm did not make a landfall in Florida, tropical storm strength winds were experienced in the state on September 2nd, Labor Day, and continued through September 4th (Mazzei et al., 2019). During this time, mandatory evacuations were issued for low-lying coastal areas, closing beaches to residents and tourists alike, and attractions throughout Florida closed temporarily (Gibson, 2019).

Beyond the initial impact, comparison of the trajectory of tourism recovery after tropical cyclones clearly shows that there are differential impacts between coastal and inland areas. Both the initial shock in the month of cyclone occurrence, and the long-term negative impacts in the months following, are much more severe for coastal counties than for inland counties both in terms of magnitude and duration. While coastal counties experience relatively large negative impacts for at least two months post-cyclone, inland areas experience smaller negative impacts, and these impacts are noticeable only in the month of cyclone occurrence. Besides this marked difference in the occurrence of negative impacts on tourism sales, there is also a remarkable difference in terms of recovery or bounce-back effects between coastal and inland counties. Namely, visual inspection of the results (Figure 3) show that there was a bounce-back or recovery effect for coastal counties three months after cyclone occurrence, but this effect is not statistically significant. In contrast, inland counties experienced a marked, statistically significant bounce-back or recovery effect beginning four months after a cyclone and lasting for a period of two months.

Coastal counties appear to exhibit a negative reputation effect in terms of a hit to the destination’s image that is not as apparent for inland counties. While both inland and coastal destinations experience the physical effects (e.g. business closures, cleanup, etc) in the month of the storm, coastal counties experience a reputation effect persisting for 3 months, suffering a loss in tourism revenues that is similar in magnitude to the loss associated with short-term physical impacts. Policy interventions to mitigate the impacts of tropical cyclones, such as government grants or loans for clean-up and rebuilding, tend to be geared toward physical impacts. However, given that our results show that in coastal areas there is a reputation effect that persists for months, there is arguably a need for longer-term relief to address the impacts of the reputation effect.

The findings suggest several policy and management implications towards a destination's recovery from a tropical cyclone. As tourism plays an important part in Florida's economy, policymakers need to be aware that there will be an acute need for economic relief among tourism operations immediately following a tropical cyclone and up to 2 months after. It may be possible to decrease the number of lags with negative impacts, or shorten the recovery period, with aggressive and creative marketing to restore the destination's image. For example, Visit Florida marketing efforts post-hurricane Irma featured articles and ads both domestically and internationally along with a coordinated social media campaign to demonstrate what areas of the state were open for business and promote the recovery efforts (Visit Florida, 2017). However, this calls for further research to examine what impacts, if any, marketing efforts may have.

While this analysis allows an assessment of the magnitude and duration of the differential impacts of tropical cyclones on the tourism economy of coastal and inland areas in a mature destination—as proxied by gross sales in tourism-related sectors—it can provide only limited insight into *why* there is a systematic difference in the impacts of tropical cyclones between inland and coastal counties. Namely, we can infer that the systematic differences observed between inland and coastal destinations are associated with the higher exposure to tropical cyclones of waterfront areas, but it would be difficult to use this analysis to provide further explanations. To do so, it would be necessary to build a panel database that includes characteristics of individual counties (beyond presence of coastline) that could explain systematic differences in the impacts of tropical cyclones. Such a database could include county-specific factors that may potentially explain systematic variation in tourism response to tropical cyclones such as physical infrastructure, social vulnerability (Emrich and Cutter, 2011) and resilience indicators (Cutter et al., 2010).

Similarly, it is likely that the impacts of tropical cyclones differ among destinations in different stages of the tourism area life cycle. Therefore, inclusion of emerging destinations in the *exploration* or *involvement* stages, as well as mature destinations in *consolidation* and *rejuvenation* stages, could provide important insights into the differential impacts of tropical cyclones on destinations at different stages of the tourism area life cycle.

One limitation of this study pertains to the tropical cyclone indicator itself, as it only accounts for the occurrence of tropical cyclones while, in essence, overlooking their intensity. While several alternative identification strategies were considered, we found that, given the relatively short span of available data, a single binary indicator provided the most reliable strategy to identify the impacts of tropical cyclones. Preliminary analyses used a categorical indicator that identified storm strength (based on maximum storm category) and a categorical indicator that distinguished between tropical storm and hurricane strength wind fields, but due to the relatively small number of events in each category, that approach did not yield satisfactory estimation results in terms of identifying impacts of cyclones to the tourism economy. Besides there being too few events in each category to provide significant results for a storm strength indicator, the indicator itself was unreliable due to the nature of the wind swath data. This exploratory process also revealed two additional rationales for selecting a binary indicator. First, due to the way that the publicly available wind swath shapefiles were constructed, storm strength could not be accurately determined for cyclones beyond Category 1 winds. The publicly-available wind swath shapefiles use three thresholds to indicate maximum sustained wind speed: 34 knots (Tropical Storm), 50 knots, and 64 knots (Category 1 Hurricane) (Emrich et al., 2020), which limits the ability to model high intensity events. Future availability of more detailed wind swath data that differentiates between multiple wind speed categories—similar to the Saffir-Simpson scale—would allow an estimation of differential impacts across tropical cyclone intensity levels. Given a way to differentiate intensity, it is expected that there would be some differences in the magnitude of the impacts across intensity levels, which may be more pronounced with Category 4 or 5 storms due to storm damage resulting in extended business interruption. Second, while it was possible to distinguish tropical storms from hurricanes, there were multiple instances of portions of counties being affected by both tropical storm and hurricane strength winds in a given storm, requiring an arbitrary judgment be made as to how to classify a particular storm for a given county.

Additionally, future research should consider variation through time by using finer data for both tourism revenues and tropical cyclones. Granularity of revenue data in terms of time is particularly important for development of precise estimates. For example, this analysis considers the month of tropical cyclone incidence as TC_t regardless of how far into that month the cyclone occurred. Thus, it is unable to differentiate TC_t months in which a cyclone occurred in the first week of the month, and those in which a cyclone occurred in the last week of the month. Weekly, or even daily, revenue data would allow analyses that estimate impacts with increased precision, and would give a more detailed picture of the impacts of tropical cyclones on the tourism economy. The more detailed picture would give better insights into short-term impacts and recovery or bounce-back effects, and shed light on the potential effectiveness of future policy responses.

Another direction for future work is conducting interviews and large scale surveys with tourism stakeholders designed to probe on their perceptions, impacts, and coping strategies in the face of tropical cyclones, as this would allow characterizing the extent of all impacts (beyond revenue losses). In addition, such efforts may provide the qualitative information needed to better characterize where short-term losses from business interruption stop and longer term losses due to reputation effect begin.

Further examination of differential spatial impacts (e.g. nearest neighbor versus distant counties) may help shed light on whether neighboring counties immediately outside a cyclone’s wind field benefit from a recovery period as well as whether there is a deflection of leisure tourism demand to distant counties. Similarly, multivariate panel data models that examine the differential impacts of tropical cyclones on tourism in contrast to other industries such as agriculture, construction, and health care, may provide insights regarding the resilience of tourism relative to other industries. A similar analysis could also be conducted to examine differences in impacts among the six tourism component subsectors to explore which types of tourism firms are most impacted.

6. Conclusion

This study estimated the revenue losses to 6 sectors in Florida's tourism economy due to the occurrence of tropical cyclones between 2008 and 2018. Based on the pooled sample of all 67 counties in Florida, USA, mean losses were estimated to be $10.1 million during the month of the storm and $12.2 million in the month following the storm. Comparing the coastal and inland county subsets, coastal counties had mean estimated losses of approximately $12.5 million in the month of the storm and persistent effects for the following 2 months, with average losses of $16.6 million and $9.7 million in the first and second months following a storm, respectively. In inland counties the tropical cyclone indicator was significantly different from zero for the month of the storm as well as the fourth and fifth months post-cyclone, with estimated losses of approximately $7.5 million and a positive recovery impact in the fourth ($1.6 million) and fifth ($2.7 million) months. These results suggest that Florida's coastal counties are most impacted in terms of tourism-related losses, and suggest there is a reputation effect that disproportionately affects waterfront destinations. The approach presented here is flexible and could be used to measure the impacts of cyclones on other outcome variables of interest that vary across discrete spatial units, such as hotel occupancy rates (by city or county) or passenger arrivals (by airport).

References

Abbot, J. (2019, September 6). Hurricane Dorian: Storm grazed Florida, still doused Labor Day tourism. *The Palm Beach Post*. Retrieved from https://www.palmbeachpost.com/news/20190906/hurricane-dorian-storm-grazed-florida-still-doused-labor-day-tourism

Atzori, R., Fyall, A., Miller, G. (2018). Tourist responses to climate change: Potential impacts and adaptation in Florida's coastal destinations. *Tourism Management*. 69: 12-22.

Bang Vu, T., Iksoon Im, E., Thompson, R. R., & DeWitt, T. (2017). The interaction of tourism and cyclone activity in East Asia: Sustainability and disasters. *Tourism Review International*, *21*(4), 379–393. https://doi.org/10.3727/154427217X15094520591358

Baum, Christopher F. (2000). XTTEST3: Stata module to compute Modified Wald statistic for groupwise heteroscedasticity. *Statistical Software Components S414801*. Boston College Department of Economics.

Beck, Earl R. (1982). German tourists in Florida: A two century record. *Florida Historical Quarterly*. 61.2: 162–80.

Becken, S. (2010). The importance of climate and weather for tourism: literature review. *Land Environment & People*.

Becken, S. and Hughey, K.F.D. (2013). Linking tourism into emergency management structures to enhance disaster risk reduction. *Tourism Management*. 36: 77-85.

Bigano A, Goria A, Hamilton JM, Tol RSJ (2005) The effect of climate change and extreme weather events on tourism. In: Lanza A, Markandya A, Pigliaru F (eds) *The economics of tourism and sustainable development*. Edward Elgar Publishing

Burrus Jr., R.T., Dumas, C.F., Farrell, C.H., Hall Jr., W.W. (2002). Impact of low-intensity hurricanes on regional economic activity. *Natural Hazards Review*. 3(3): 118-125.

Butler, R. (1980). The concept of a tourist area cycle of evolution: implications for management of resources. *Canadian Geographer*. 24: 5e12.

Butler, R. (2012). "Mature tourist destinations: can we recapture and retain the magic?". In: *Renovación y reestructuración de destinos turísticos en áreas costeras: marco de análisis, procesos, instrumentos y realidades*. J. Fernando Vera Rebollo, Isabel Rodríguez Sánchez (eds.). Spain. Valencia : Publicacions de la Universitat de València. ISBN 978-84-370-8863-1, pp. 19-36.

Cahyanto, I., Pennington-Gray, L., Thapa, B., Srinivasan, S., Villegas, J., Matyas, C., Kiousis, S. (2016). Predicting information seeking regarding hurricane evacuation in the destination. *Tourism Management*. 52: 264-275.

Chandler, J.A. (2004). An analysis of the economic impact of hurricanes Dennis, Floyd, and Irene on North Carolina's lodging industry. *Journal of Hospitality & Tourism Research*. 28(3): 313-326.

Choi, D., Lee, S., Singal, M. (2019). An exploratory temporal analysis of the lodging market and state economic recovery from Hurricane Sandy (The lodging market recovery from Hurricane Sandy). *International Journal of Contemporary Hospitality Management*. 31(5): 2074-2094.

Cutter, S.L., Burton, C.G., Emrich, C.T. (2010) Disaster resilience indicators for benchmarking baseline conditions. *Journal of Homeland Security and Emergency Management.* 7(1): 51.

Cuttler, M.V.W., Hansen, J.E., Lowe, R.J., Drost, E.J.F. (2018). Response of a fringing reef coastline to the direct impact of a tropical cyclone. *Limnology and Oceanography Letters*. 3: 31-38.

Dinan, T. (2017). Projected increases in hurricane damage in the United States: the role of climate change and coastal development. *Ecological Economics*, *138*, 186-198.

Emrich, Christopher T., Alvarez, Sergio, Knox, Claire Connolly, Sadiq, Abdul A., Zhou, Yao. Hurricane Irma and cascading impacts. 123-154. in *U.S. Emergency Management in the 21st Century From Disaster to Catastrophe*. Eds, Claire B. Rubin and Susan L. Cutter. Routledge. 2020.

Emrich, C.T., and Cutter, S.L. (2011) Social vulnerability to climate-sensitive hazards in the southern United States. *Weather Climate and Society*, 3(3): 193-208.

Ewing, B.T., Kruse, J.B., Thompson, M.A. (2010). Measuring the regional economic response to Hurricane Katrina. *CESifo Forum*, ISSN 2190-717X, ifo Institut für Wirtschaftsforschung an der Universität München, München. 11(2): 80-85.

Ewing, B. T., Liang, D., Cui, Y. (2014). A Time Series Approach to Examining Regional Economic Resiliency to Hurricanes. *American Journal of Economics and Sociology*. (73)2.

Exec. Order No. 19-189. FL. (August 28, 2019).

Exec. Order No. 19-189. FL. (August 29, 2019).

Fitchett, J.M., Hoogendoorn, G. and Swemmer, A.M. (2016). Economic costs of the 2012 floods on tourism in the Mopani District Municipality, South Africa. *Transactions of the Royal Society of South Africa*. 71(2): 187-194.

Florida Climate Center. (2020). Hurricanes. Retrieved from https://climatecenter.fsu.edu/topics/hurricanes

Forster, J., Schuhmann, P.W., Lake, I.R. *et al.* (2012). The influence of hurricane risk on tourist destination choice in the Caribbean. *Climatic Change* 114**:** 745–768.

Fox, J.T. (2018, August 20). One year later, Florida hotels take stock of Hurricane Irma's effects. *Hotel Management*. Retrieved from https://www.hotelmanagement.net/operate/one-year-later-florida-hotels-take-stock-irma-s-effects

FRPC (Florida Regional Planning Council). (2012). “Florida statewide regional evacuation study program.” Available at: http://www.sfrpc.com/sresp.htm

Gibson, K. (2019, September 3). Disney World, Legoland and other Orlando tourist parks close as Dorian nears Florida. *CBS News*. Available at: https://www.cbsnews.com/news/hurricane-dorian-florida-closures-disney-world-universal-studios-legoland-other-orlando-tourist-attractions-today/

Gössling S, Hall CM (2006) Uncertainties in predicting tourist flows under scenarios of climate change. *Climatic Change*. 79:163–173

Granvorka, C., & Strobl, E. (2013). The Impact of Hurricane Strikes on Tourist Arrivals in the Caribbean. *Tourism Economics*, *19*(6), 1401–1409. https://doi.org/10.5367/te.2013.0238

Grinsted, A. et al. (2019). Normalized US hurricane damage estimates using area of total destruction, 1900-2018. *PNAS*.

Greene, W.H. (2012). *Econometric analysis*. Pearson. pp 386-387.

Hausman, J. (1978). Specification tests in econometrics. *Econometrica*. 46(6): 1251-1271.

Hoegh-Guldberg, O., et al. (2018). Impacts of 1.5ºC global warming on natural and human systems. In: *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening* *the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty*. Masson-Delmotte, V., et al. (eds.). In Press.

Hsu, S. A., & Yan, Z. (1998). A note on the radius of maximum wind for hurricanes. *Journal of coastal research*. 14(2).

Hurricane Research Division. (2019). How many direct hits by hurricanes of various categories have affected each state? Retrieved from: http://www.aoml.noaa.gov/hrd/tcfaq/E19.html

IPCC. (2019). *IPCC Special Report on the Ocean and Cryosphere in a Changing Climate*. H.-O. Pörtner, D.C. Roberts, V. Masson-Delmotte, P. Zhai, M. Tignor, E. Poloczanska, K. Mintenbeck, A. Alegría, M. Nicolai, A. Okem, J. Petzold, B. Rama, N.M. Weyer (eds.). In press.

Kim, H., Marcouiller, D.W. (2015). Considering disaster vulnerability and resiliency: the case of hurricane effects on tourism-based economies. *The Annals of Regional Science.* 54: 945–971.

Klomp, Jeroen (2016) Economic development and natural disasters: A satellite data analysis. *Global Environmental Change*. 36: 67-88.

Klotzbach, P. J., Bowen, S. G., Pielke Jr, R., & Bell, M. (2018). Continental US hurricane landfall frequency and associated damage: Observations and future risks. *Bulletin of the American Meteorological Society*, *99*(7), 1359-1376.

Kozak, M. and Martin, D. (2012). Tourism life cycle and sustainability analysis: Profit-focused strategies for mature destinations. *Tourism Management*. 33: 188-194.

Knutson, T.R. et al. (2013). Dynamical downscaling projections of twenty-first-century atlantic hurricane activity: CMIP3 and CMIP5 model-based scenarios. *J. Clim*. 26: 6591–6617.

Landsea, C.W. (1993). *A climatology of intense (or major) Atlantic hurricanes*. Mon. Wea. Rev., 121, pp.1703-1713.

Larson, S. and McDonald, B. (2020) When the beaches close: Impact of COVID-19 upon county fiscal health in Florida. Available at SSRN: https://ssrn.com/abstract=3594898 or http://dx.doi.org/10.2139/ssrn.3594898

Leatherman, S. P., Zhang, K., Douglas, B. C. (2000). Sea level rise shown to drive coastal erosion. *EOS*. 81(6): 55-57.

Li, L., Chakraborty, P. (2020). Slower decay of landfalling hurricanes in a warming world. *Nature* 587, 230–234. https://doi.org/10.1038/s41586-020-2867-7

Marsooli, R., Lin, N., Emanuel, K., & Feng, K. (2019). Climate change exacerbates hurricane flood hazards along US Atlantic and Gulf Coasts in spatially varying patterns. *Nature communications*, *10*(1), 1-9.

Marzeion, B. and Levermann, A. (2014). Loss of cultural world heritage and currently inhabited places to sea-level rise. *Environmental Research Letters*, 9(3), 034001, doi:10.1088/1748-9326/9/3/034001.

Mazzei, P. and Bogel-Burroughs, N. (2019, September 6). Storm could swamp the coast from Florida to Virginia. *The New York Times*. Retrieved from https://www.nytimes.com/2019/09/04/us/hurricane-dorian-updates.html

McDermott, T.K.J., Barry, F., Tol, R.S.J. (2014). Disasters and development: Natural disasters, credit constraints, and economic growth. *Oxford Economic Papers*. 66: 750-773.

Monahan, W.B., Rosemartin, A., Gerst, K.L., Fisichelli, N.A., Ault, T., Schwartz, M.D., Gross, J.E., and Weltzin, J.F. (2016). Climate change is advancing spring onset across the U.S. national park system. *Ecosphere*. 7(10): e01465.10.1002/ecs2.1465

National Hurricane Center. (2019). NHC data in GIS formats. Retrieved from https://www.nhc.noaa.gov/gis/

National Hurricane Center. (2020). Tropical cyclone climatology. Retrieved from https://www.nhc.noaa.gov/climo

NOAA. (2020). Tourism and recreation. Retrieved from https://coast.noaa.gov/states/fast-facts/tourism-and-recreation.html

Pant, S., & Cha, E. J. (2019). Potential changes in hurricane risk profile across the United States coastal regions under climate change scenarios. *Structural Safety*, *80*, 56-65.

Pielke, R. A. and Landsea, C. W. (1998). Normalized hurricane damages in the United States: 1925–95. *Weather Forecast*. 13: 621–631.

Pinelli, J.P., Pita, G., Gurley, K., Torkian, B., Hamid, S., Subramanian, C. (2011). Damage characterization: Application to Florida Public Hurricane Loss Model. *Natural Hazards Review*. 12(4): 190-195.

Prideaux, B., Coghlan, A., & Falco-Mammone, F. (2008). Post Crisis Recovery. *Journal of Travel & Tourism Marketing*, *23*(2–4), 163–174. https://doi.org/10.1300/J073v23n02_13

Revels, T.J. (2011). *Sunshine Paradise: A History of Florida Tourism*. University Press of Florida, Gainesville.

Rosselló, J., Becken, S., Santana-Gallego, M. (2020). The effects of natural disasters on international tourism: A global analysis. *Tourism Management*. 79: 104080.

Saunders, M., Lea, A. (2005). Seasonal prediction of hurricane activity reaching the coast of the United States. *Nature*. 434: 1005–1008.

Schott, T., et al. (2019). The Saffir-Simpson Hurricane Wind Scale. *National Hurricane Center*. Available at: https://origin.www.nhc.noaa.gov/pdf/sshws.pdf

Scott, D., Simpson, M.C., and Sim, R. (2012). The vulnerability of Caribbean coastal tourism to scenarios of climate change related sea level rise. *Journal of Sustainable Tourism*. 20(6): 883–898.

Scott, D. and Verkoeyen, S. (2017). Assessing the climate change risk of a coastal-island destination. In: *Global climate change and coastal tourism: recognizing problems, managing solutions and future expectations*. Jones, A. M. Phillips, M. (eds.). Centre for Agriculture and Biosciences International (CABI), Wallingford, UK, pp. 62–73, doi:10.1079/9781780648439.0062.

Scott, D., Steiger, R., Knowles, N., and Fang, Y. (2020). Regional ski tourism risk to climate change: An inter-comparison of Eastern Canada and US Northeast markets. *Journal of Sustainable Tourism*. 28(4): 568-586.

Schumacher, Ingmar and Strobl, Eric (2011) Economic development and losses due to natural disasters: The role of hazard exposure. *Ecological Economics*. 72: 97-105.

Skidmore, Mark and Toya, Hideki (2002) Do natural disasters promote long-run growth? *Economic Inquiry*. 4(4): 664-687.

Stapleton, C. (2019, September 21). Hurricane Dorian: Storm left ocean murky, leaves scuba, fishing charters docked. *The St. Augustine Record*. Retrieved from https://www.staugustine.com/news/20190921/hurricane-dorian-storm-left-ocean-murky-leaves-scuba-fishing-charters-docked

Sydnor-Bousso, S., Stafford, K., Tews, M., Adler, H. (2011). Toward a resilience model for the hospitality & tourism industry. *Journal of Human Resources in Hospitality & Tourism*. 10: 195-217.

Toya, Hideki and Skidmore, Mark (2007) Economic development and the impacts of natural disasters. *Economic Letters.* 94: 20-25.

Trenberth, K. E., Cheng, L., Jacobs, P., Zhang, Y., & Fasullo, J. (2018). Hurricane Harvey links to ocean heat content and climate change adaptation. *Earth's Future*, *6*(5), 730-744.

United Nations. (2017). Factsheet: People and oceans. In Proceedings of the Ocean Conference, New York, NY, USA, 5–6 June 2017; Available online: https://www.un.org/sustainabledevelopment/wp-content/uploads/2017/05/Ocean-fact-sheet-package.pdf (accessed on 9 October 2019).

Visit Florida. (2017). Post-Irma marketing plan. Available online: https://www.visitflorida.org/media/39893/post-irma-marketing-plan-industry.pdf

Visit Florida. (2018). 2018-19 marketing plan. Available online: https://www.visitflorida.org/media/51868/vf-marketing-plan_2018-19.pdf

Visit Florida. (2020). Retrieved from https://www.visitflorida.org/

Vousdoukas, M.I., Ranasinghe, R., Mentaschi, L. et al. (2020). Sandy coastlines under threat of erosion. Nature Climate Change. 10: 260–263. https://doi.org/10.1038/s41558-020-0697-0

Yang, Dean (2008) Coping with Disaster: The Impact of Hurricanes on International Financial Flows, 1970-2002. *The B.E. Journal of Economic Analysis & Policy*. 8:1 (Advances), Article 13.

Supplementary Table

	All Counties	Inland	Coastal
TC_t	-10.1459** (3.8341)	-7.4659* (4.0897)	-12.5266** (5.6536)
TC_{t-1}	-12.23*** (4.1469)	-3.0753 (1.9508)	-16.5855** (6.1792)
TC_{t-2}	-6.9257* (3.6128)	-1.9843 (1.6637)	-9.7018* (5.4984)
TC_{t-3}	3.2361 (2.4979)	-2.0889 (1.6644)	6.6026 (4.7196)
TC_{t-4}	-3.9209 (3.6487)	1.6359** (0.7944)	-7.807 (5.5793)
TC_{t-5}	-0.8109 (2.8634)	2.7871** (1.2887)	-2.6669 (3.9293)
TC_{t-6}	4.2046 (3.8551)	5.0077 (3.8222)	3.8927 (4.6417)
Florida unemployment	-15.5933*** (3.2442)	-5.5464* (2.9101)	-22.6079*** (4.8467)
Constant	250.4045*** (21.9912)	119.1371*** (21.006)	361.5346*** (34.5781)
Jan-09	Base		Base
Feb-09	4.4916* (2.3227)		6.4768 (4.3793)
Mar-09	10.7912*** (3.2549)		16.8587*** (5.6827)
Apr-09	28.2955*** (5.8492)		40.9955*** (7.5761)
May-09	23.8497*** (4.7370)		34.1124*** (6.1046)
Jun-09	18.9204*** (3.8788)		25.8290*** (4.9026)
Jul-09	22.2255*** (4.7264)		30.5826*** (5.4842)
Aug-09	25.0009*** (4.6970)		36.0905*** (6.0531)
Sep-09	17.7807*** (3.5739)		24.6232*** (4.4324)
Oct-09	16.3087*** (3.2595)		22.0420*** (3.7229)
Nov-09	26.8510*** (5.3441)		36.7377*** (6.3763)
Dec-09	29.5608*** (5.6709)		42.9440*** (7.6211)
Jan-10	41.5453*** (8.8424)		61.5646*** (13.4901)
Feb-10	36.3589*** (7.4976)		52.7272*** (11.0168)
Mar-10	38.4133*** (7.7488)		58.1721*** (11.5529)
Apr-10	51.2566*** (10.2789)		74.6740*** (14.2501)
May-10	39.4211*** (7.6033)		56.1149*** (9.8216)
Jun-10	28.7726*** (5.8313)		39.9699*** (6.2134)
Jul-10	31.1448*** (6.3343)		43.3286*** (6.9806)
Aug-10	33.1886*** (6.5087)		46.6762*** (7.3687)
Sep-10	23.0384*** (4.8779)		31.3966*** (5.0064)
Oct-10	22.2063*** (4.3859)		29.6694*** (4.7849)
Nov-10	30.3745***		41.5749***

	(6.2407)		(7.2816)
Dec-10	22.6928*** (4.9949)		30.6574*** (5.5171)
Jan-11	41.1287*** (8.6942)		58.4625*** (12.4924)
Feb-11	35.8645*** (7.4413)		51.2389*** (10.2873)
Mar-11	41.8292*** (7.9960)		60.6268*** (11.1905)
Apr-11	55.4872*** (11.8099)		78.8831*** (15.6241)
May-11	43.8467*** (8.4540)		61.5923*** (10.6153)
Jun-11	32.4036*** (6.2567)		45.5889*** (7.2819)
Jul-11	31.6356*** (6.2735)		43.7091*** (6.8467)
Aug-11	30.8318*** (5.8595)		43.5552*** (6.8883)
Sep-11	16.9131*** (3.5032)		22.6378*** (3.5562)
Oct-11	11.7472*** (2.8039)		14.4438*** (3.0437)
Nov-11	15.5784*** (3.4088)		19.5978*** (2.8745)
Dec-11	9.2123*** (2.5979)		10.6537*** (1.6857)
Jan-12	41.4017*** (9.7634)		52.2146*** (12.7448)
Feb-12	23.5358*** (4.9546)		34.9702*** (7.6123)
Mar-12	24.5816*** (4.9693)		35.5482*** (6.8116)
Apr-12	44.4944*** (9.4177)		62.9212*** (11.9162)
May-12	30.2495*** (5.9086)		42.6198*** (7.2944)
Jun-12	21.5393*** (5.0470)		27.9013*** (5.6679)
Jul-12	27.7542*** (6.3684)		36.6096*** (8.1785)
Aug-12	23.5831*** (5.6790)		31.5146*** (7.0347)
Sep-12	6.1883** (2.5872)		6.9378* (3.9346)
Oct-12	5.4501 (3.3858)		5.7483 (5.174)
Nov-12	10.7790*** (2.5599)		11.6318*** (3.5366)
Dec-12	1.9127 (2.0915)		2.4155 (3.5996)
Jan-13	20.3663*** (6.3212)		29.4697** (10.8862)
Feb-13	17.5594*** (4.1406)		25.7633*** (6.7283)
Mar-13	12.0151*** (2.7349)		17.3337*** (4.1494)
Apr-13	34.8721*** (7.2615)		49.9648*** (10.044)
May-13	13.0119*** (2.8952)		16.9049*** (3.3898)
Jun-13	8.2670** (3.5514)		7.9251 (4.7506)
Jul-13	15.6001*** (5.2409)		18.6166** (7.8595)
Aug-13	5.0397 (4.3794)		5.4121 (7.844)
Sep-13	-11.4404***		-19.3849**

	(4.4559)		(8.41)
Oct-13	-11.3220*** (3.4085)		-18.8272*** (6.5189)
Nov-13	-7.1311** (2.6874)		-13.8436** (5.1096)
Dec-13	-12.4666*** (3.1368)		-21.6198*** (5.489)
Jan-14	8.5033** (4.7426)		12.9495 (8.8373)
Feb-14	9.6111** (4.4491)		14.2832* (7.9865)
Mar-14	6.0007** (2.3811)		8.7565** (3.8145)
Apr-14	26.9417*** (6.0233)		38.8545*** (8.5928)
May-14	13.1560*** (3.8529)		16.8723*** (4.1751)
Jun-14	-0.6337 (3.3711)		-2.0143 (6.2723)
Jul-14	5.7320 (4.8836)		6.6996 (8.8778)
Aug-14	-0.3328 (5.1819)		-0.6504 (10.0117)
Sep-14	-11.3745** (4.9228)		-18.3737* (9.1462)
Oct-14	-19.2901*** (5.3438)		-31.0720*** (9.3232)
Nov-14	-6.6932** (3.7229)		-13.0750* (6.421)
Dec-14	-4.6223 (2.8265)		-9.1030* (4.7863)
Jan-15	8.1393 (5.6774)		12.7541 (10.6831)
Feb-15	5.4403* (3.1484)		8.7122 (5.5491)
Mar-15	1.6093 (3.0403)		1.5975 (4.2063)
Apr-15	22.5614*** (5.8559)		33.0021*** (8.2979)
May-15	7.7716** (3.4002)		10.6713** (4.8848)
Jun-15	-5.6819 (4.1421)		-8.1854 (7.7217)
Jul-15	-6.2968 (5.8933)		-10.2668 (10.9686)
Aug-15	-4.0460 (6.2142)		-6.4546 (11.7925)
Sep-15	-12.6440** (5.6826)		-19.7770* (10.5331)
Oct-15	-24.4012*** (6.6718)		-38.8317*** (11.7313)
Nov-15	-10.8851** (4.5777)		-19.3820** (7.9232)
Dec-15	-16.8222*** (4.5114)		-27.4514*** (7.6486)
Jan-16	5.1027 (5.9512)		7.4776 (10.946)
Feb-16	-0.3576 (2.6404)		0.2040 (4.6959)
Mar-16	1.8643 (3.1629)		2.6404 (4.7032)
Apr-16	20.3789*** (5.8490)		29.2597*** (8.2185)
May-16	1.9776 (3.3675)		2.2042 (5.9235)
Jun-16	-4.0385 (5.3733)		-9.4375 (9.084)
Jul-16	-1.5269		-6.5630

	(6.4144)		(11.6126)
Aug-16	9.2425 (6.7078)		12.5310 (12.1264)
Sep-16	-17.6604*** (6.5163)		-31.5228** (12.0241)
Oct-16	-4.3220 (7.1072)		-13.3114 (11.5429)
Nov-16	-1.0348 (5.3855)		-9.3070 (8.416)
Dec-16	-18.6206*** (4.0339)		-32.0897*** (7.4387)
Jan-17	14.7305** (6.8338)		21.6010* (11.5771)
Feb-17	5.7430*** (3.8813)		7.5245 (6.0901)
Mar-17	-3.0189** (1.4869)		-3.4331 (2.2237)
Apr-17	20.9331*** (5.6349)		28.9570*** (7.6357)
May-17	8.4963* (4.8200)		8.6623 (6.6496)
Jun-17	-8.9008 (5.9033)		-16.4724 (10.4923)
Jul-17	-9.2616 (7.3142)		-17.5862 (13.337)
Aug-17	0.1647 (7.5389)		0.4425 (14.5714)
Sep-17	-13.7293* (7.5583)		-25.8481* (13.331)
Oct-17	-13.8684* (8.0097)		-29.4509** (14.4556)
Nov-17	1.9966 (6.6301)		-4.3609 (10.2196)
Dec-17	-19.8202*** (5.3366)		-36.3857*** (9.3593)
Jan-18	19.5980 (12.5111)		30.7081 (22.6334)
Feb-18	7.6902** (4.0387)		8.3558 (6.7907)
Mar-18	[1]Omitted		[1]Omitted
Apr-18	34.9676*** (9.4560)		47.7216*** (11.9922)
May-18	12.7335** (6.7950)		13.8816 (9.1929)
Jun-18	-4.7997 (6.8065)		-11.5067 (12.0983)
Jul-18	7.9976 (9.1858)		8.9301 (16.4502)
Aug-18	-3.4900 (8.1070)		-7.1836 (15.4014)
Sep-18	-21.3761*** (7.9993)		-34.6181** (14.7518)
Oct-18	-23.9213*** (8.4635)		-41.3537** (15.1719)
Nov-18	-4.4050 (6.8639)		-16.2681 (11.3402)
Dec-18	-41.2531*** (10.3222)		-71.3928*** (17.9376)

****p<0.01, **p<0.05, *p<0.10, [1]Omitted due to collinearity*