The impact of hurricane strikes on cruise ship and airplane tourist arrivals in the Caribbean

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Abstract

We investigate the impact of hurricanes on airplane and cruise ship arrivals in the Caribbean. To this end we construct a monthly panel of airline and cruise ship arrivals and hurricane destruction, and employ a panel vector autoregressive model with an exogenous shock (VARX) to quantify the dynamic effects of tourist arrivals after a hurricane for 18 Caribbean countries over the period 2000 to 2013. The results suggest an immediate decline in the month of a strike and up to one month after on cruise ship (2.33 and 1.21 percentage points) and airplane (0.57 and 0.27 percentage points) arrivals. Moreover, a strong recovery in airplane arrivals in months 3 to 6 following a hurricane was sufficient to induce a net positive effect of around 2 percentage points of total tourist arrivals into the region.

1 Introduction

Tourism is among the largest and fastest growing industries globally. For example, in 2019 global travel and tourism GDP growth was 3.9% and accounted for 10.4% of total GDP and 10% of total employment (WTTC 2019). Importantly, tourism is not a single commodity, but a dynamic and complex industry that is driven by both the local supply of tourism services as well as the global demand for these. As such the sector is shaped by a wide range of factors, which makes the sector highly volatile and susceptible to a growing number of exogenous shocks. One particularly important one is that of natural disasters (Okumus et al. (2005) and Ritchie and Jiang (2019)), where such catastrophes can induce considerable physical damage the local tourist infrastructure, leading potentially to substantial falls in visitor arrivals (Peters and Pikkemaat (2005) and Huang and Min (2002)). As a matter of fact, climate change and related natural disasters are identified as major challenges to grow the sector globally (Buckley et al. (2015)). Understanding to what extent these adverse events actually do affect the inflow of tourists would help affected economies to manage and mitigate their negative implications when a crisis does occur. However, there is a paucity of research on the impact of harmful shocks in general, and specifically with regard to natural disasters, on the tourism sector (Faulkner (2001)). In this paper we address this gap by studying the impact of hurricanes on tourism arrivals in Caribbean islands.

Small Island Developing States (SIDS) are especially vulnerable to natural disasters (Thomas, Baptiste, Martyr-Koller, Pringle, and Rhiney (2020)), while at the same time highly dependent on tourism, in particular on international travellers rather than the domestic market (Forster et al. (2012)). In this regard, Caribbean SIDS are identified as the most tourism dependent countries globally (Mooney and Zegarra (2020)). In 2019, for instance, travel and tourism in the region directly contributed to 13.9% of total GDP and 15.2% of total employment (WTTC 2019), and in some islands was more than 25% of GDP and in excess of 50% of employment (WTTC 2018).[1]

[1]The Bahamas (51% of GDP), Antigua and Barbuda (56% of GDP), Anguilla (61% of GDP), and the

The Caribbean is also known for being the most disaster prone region in the world on account of the high number of hurricanes experienced (Rasmussen (2004)).[2] For example, since 1970 the region has suffered more than 250 natural disasters, mainly storms, that have killed over 12,000 people and affected over 12 million, with estimated annual average damages of 1% of the region's GDP (Mejia, 2014). Acevedo et al. (2013) point out that most Caribbean countries have a hurricane probability above 10% each year, while Sealy and Strobl (2017) state that there are on average three hurricanes per year that come within 100 km of at least one country/territory. Such storms are likely to be particularly damaging to the tourism industry in Caribbean SIDS in that it is generally the region's coastal attractions and amenities on which tourism is typically founded, but coastal areas are also most likely to suffer the most damage from tropical storms. The possibility that with climate change the frequency and intensity of hurricanes in the Caribbean is likely to increase (Knutson et al. (2010) and Emanuel (2013)) will only further increase the potential vulnerability of the tourism industry in the region.

The aim of this paper is to add to the scarce literature on adverse shocks to the tourism sector and how these shocks affect visitor arrivals on a number of fronts using the case study of Caribbean SIDS. Firstly, existing papers focus on specific events or places rather than the quantitative impact over large temporal and spatial areas. Here we focus on a large set of SIDS in the Caribbean over a time period that encompasses several damaging tropical storms. Secondly, the small current literature has solely focused on the impact of natural disasters on air arrivals, but ignored an important segment of the tourism market, namely cruise tourism. To address these issues we compile a monthly data set of air and cruise ship tourist arrivals and couple this with a measure of hurricane destruction based on the physical features of the storms and pre-event population exposure, for 18 SIDS covering 14 years (2000-2013). We then employ a panel vector autoregressive model with an exogenous

British Virgin Islands (98.5% of GDP) which is the highest share of tourism income as a percentage of GDP worldwide (WTTC 2018).

[2]Rasmussen (2004) found that 6 of the top 10 disaster-prone countries globally are in the Eastern Caribbean, while all Caribbean countries were in the top 50.

shock to causally identify and quantify the effect that hurricanes have on the two tourist segments.[3] The data input consists of a monthly panel of 18 Caribbean countries covering 14 years from 2000-2013.

Over the period of study (2000-2013), based on data from the Caribbean Tourism Organization (CTO) Caribbean countries received a grand total of 350 million tourist arrivals. The region received a larger number of cruise than plane tourists (180 million versus 168 million). Moreover, country differences exists in that the Bahamas, Dominica, Netherlands Antilles and St Kitts and Nevis were the most popular islands for cruise ship travellers, while Trinidad and Tobago and the Dominican Republic saw the smallest number. Moreover, the Dominican Republic had the largest share of tourist arrivals in the region with air arrivals being higher than cruise arrivals.

The rest of this paper is structured as follows. Section 2 presents the theoretical and empirical literature. Section 3 presents the description of the data. Section 4 introduces the econometric methodology. Section 5 presents the results of the analysis, followed by a discussion Section 6. Lastly, section 7 offers some concluding remarks.

2 Literature Review

2.1 The Impact of Natural Disasters on Tourist Arrivals

While there is no specifically developed theoretical framework on the impact of natural disasters on tourism arrivals, the existing literature does highlight several reasons why visitation to disaster areas decline in their immediate aftermath. The most direct reason relates to the damage inflicted by a natural disaster that prevents the affected destination from

[3]Panel VARX models have been used to study the economic impact of natural disasters. For example, Fomby et al. (2009) used a panel VARX model to study the impact of natural disasters (earthquakes, floods, droughts, and storms) on the GDP growth of 84 countries. Mohan et al. (2018) studied the impact of hurricanes on the different components of GDP in 21 Caribbean islands. Mejia (2014) investigated natural disasters (hurricane and floods) and their impact on per capita GDP and the debt to GDP ratio in 12 Caribbean countries. Ouattara et al. (2018) measured the impact of hurricanes on government spending in a set of Caribbean countries.

carrying out tourism activity. The exposure of tourism to natural disasters may be linked to the attractiveness of many high-risk exotic locations, where natural disasters such as hurricanes, avalanches, and volcanic activity are likely to occur (Murphy and Bayley (1989)). Natural disasters pose significant physical damage to infrastructure including airports, sea ports, roads, hotels, attractions, and environmental amenities, which reduces the country's ability to cater to tourist needs and its attractiveness, at least in the short term (Ghobarah et al. (2006) and Parajuli and Haynes (2016)).

Psychological factors and persons' risk perceptions associated with media coverage that show loss of life and human suffering and economic and social disruption can also spur negative publicity about a destination and reduce arrivals until pre-disaster conditions resume (Sönmez et al. (1999)). Travellers may also choose not to visit a disaster struck destination because of ethical concerns as they feel that they may obstruct the recovery effort and place an additional burden on the country's resources and infrastructure (Becken et al. (2015)). The risk of a natural disaster occurrence without its actual occurrence can also reduce visitor arrivals since travel plans are made by taking potential risks into account (K.-S. Park and Reisinger (2008) and Becken et al. (2015)). Additionally, tourists may avoid a disaster prone area since they are unfamiliar with the destination and its natural forces and are therefore more easily exposed to the threat of natural disasters (Drabek (1995) and Rittichainuwat (2006)). The amount of risks an international traveller is willing to take is also influenced by their cultural, demographic and economic background, where low income tourists are more concerned about natural disasters because they have less money and therefore avoid making risky travel plans (K. Park and Reisinger (2010)).

Among the handful of empirical studies the evidence demonstrates that natural disasters pose a threat to international tourist arrivals. Rosselló et al. (2020) investigated natural and man-made disasters using a gravity model for international tourism flows to quantify the effects of different types of natural and man-made disasters on tourist arrivals to the affected countries. They provided evidence that the occurrence of different types of disaster events change international tourist inflows differently where natural disasters more negatively affect arrivals. Ma et al. (2020) also examined natural and man-made events looking at earthquakes and terrorist attacks. They adopted of a difference-in-difference research method and online review data from TripAdvisor to comparatively analyse the effects of catastrophic events with varying natures, frequencies, and intensities on tourism. The results show that earthquakes had a greater effect on reducing the number of visitors. In a study of hurricanes across Caribbean countries, Granvorka and Strobl (2013) derived a hurricane destruction index based on wind speed to estimate the impact of hurricanes and concluded that an average hurricane strike caused total (air and cruise) arrivals to be about 2% lower than they would have been had no strike occurred. These studies generally consider a single type of tourist or total tourism and there is little comparison of how different categories of tourists respond to or recover from negative events, such as, for example, air versus cruise travellers (Ritchie and Jiang (2019)).

2.2 Hurricanes and Tourist Arrivals

A tropical cyclone is the meteorological term for a storm system that forms in the tropics. They are referred to as hurricanes if they are formed in the North Atlantic and are of sufficient strength measured by wind speed, generally at least 119 km/h. Hurricanes in the Caribbean develop from a low pressure system generally off the coast of Africa from a tropical storm which, in turn, begins as a tropical depression. The Atlantic Hurricane season generally runs from June to November, but can start as early as May. Hurricanes are extremely destructive. Their strong winds may cause damage to agricultural crops and buildings, homes, and infrastructure. They are accompanied by heavy rainfall, which results in flooding, landslips, and landslides. They also bring with them storm surges as their high winds push on the ocean's surface causing coastal erosion, property damage, and salt contamination. The extent of potential damage caused by a hurricane depends on various factors, including where it strikes and what is located in that area, the slope of the continental shelf, and the shape of the coastline in the landfall region. Destruction is typically measured in terms of wind speed. It is generally agreed that considerable damage occurs when a hurricane reaches speeds of at least 178 km/h in approaching the coast and/or making landfall, where 178 km/h refers to level three on the widely used Saffir-Simpson tropical storm severity scale.

In relation to tourist arrivals, a priori one should expect the impact of hurricanes to take place via two channels. Hurricanes bring with them direct costs, such as the destruction of infrastructure, coastal degradation, and tourism amenities, which will lower the quality of the location as a tourist destination, at least in the short term. The potential fall in tourist arrivals in the Caribbean after a hurricane strike is likely due to damages to infrastructure and a general increase in economic and social disruption and safety concerns which can reduce the region's ability to accommodate tourists and its attractiveness. Sealy and Strobl (2017) found expected losses from hurricanes in the Bahamas of about 2% of coastal property including hotels and other tourist accommodations and attractions, where more devastating strikes could cause up to 34% in losses. This destruction may translate into a fall in tourist arrivals. Reports show that after Hurricane David in 1979, Dominica experienced a 30% decline in tourist arrivals as a consequence of destruction to infrastructure and facilities (Benson et al. (2001)). More recently in 2017, Hurricane Irma sharply reduced American visitors by 79% in Sint Maarten and 45.6% in Puerto Rico compared to the previous year (CTO 2019). Hurricanes in the Caribbean therefore represent a major shock to tourism and can significantly affect visitor arrivals.

On the other hand, one might anticipate hurricane strikes increasing the subjective perceived probability of future hurricanes, further discouraging tourists who are on the margins of choosing the affected country relative to alternative destinations, thereby reducing future arrivals. In relation to the Caribbean a strong tourist economy cannot grow unless potential tourists perceive the destination as safe place to vacation. A particularly destructive hurricane that caused severe damage, loss of life, and suffering may create a lasting image that a Caribbean destination is a dangerous and risky place for vacation. Forster et al.

(2012) showed that in Anguilla hurricane risk influenced the risk perceptions and decisions regarding holiday preferences by tourists, which can reduce international visitors.

2.3 Hurricanes and Cruise Ship versus Airplane Arrivals

The cruise industry is the fastest growing category in the leisure travel market. Since 1980 cruise tourism has become a popular alternative to air travel in the international tourism market, and has experienced an average annual passenger growth rate of approximately 7% yearly (CLIA 2017). Further, between 2005 to 2015 the demand for cruising increased by 62% (CLIA 2017). This has been driven by targeting mass numbers, new ports-of-call and expanded itineraries, an increase in demand for all-inclusive type packages and digitization of the tourism sector (Dowling (2006)). Cruises now offer, guided tours in port cities, shore excursions in visitor centers, and sometimes even overnight stays, and may therefore also contribute to the local economy.

The cruise and air arrival tourism segments differ in many ways and as such the impact of hurricanes on each segment may vary as well. The largest difference may be in terms of spending patterns, number of destinations, and length of stay. Cruise visitors generally spend relatively less in a given location, while at the same time they visit multiple destinations for a shorter period of time compared to air arrivals (CDB 2017). Airlines and airplane passengers are significantly more flexible in terms of their flights. Airlines will typically reschedule as soon as the hurricane is over, and airplane passengers are then able to arrive shortly after their initially planned arrival date. Moreover, airlines and hotels often run ad campaigns and offer discounts following hurricanes. Cruise ship passengers sleep on and travel with the ship, making any island specific discounts irrelevant. Additionally, travel during the hurricane season is already discounted for cruise passengers. Cruise ships will usually choose to either stay at sea or offer a different destination instead of visiting areas with a hurricane forecast or an area that was affected by a recent hurricane strike.

The difference in the impact of hurricanes on air versus cruise tourists is important given that the composition of cruise to air tourists has been changing in the Caribbean and their spending patterns differ significantly. More precisely, air arrivals into the region has been growing slowly compared to cruise arrivals because of intensified competition from other destinations; over the period 1989-2014 the number of air arrivals to the region grew at an average rate of 2.5% compared to 4.5% globally, while the number of cruise arrivals more than tripled ((CDB 2017)). In addition, the daily spending per person for cruise passengers in the region is on average 55% lower than the spending per person for air tourists ((CDB 2017)).

3 Data

3.1 Tourism Data

The CTO was used as our source of tourist arrivals data.[4] The CTO provides data on the number of monthly cruise ship and airplane arrivals for 18 islands in the Caribbean from the year 2000. Additionally, the CTO collates the total annual number of tourists per island by country/region of origin for airplane arrivals.

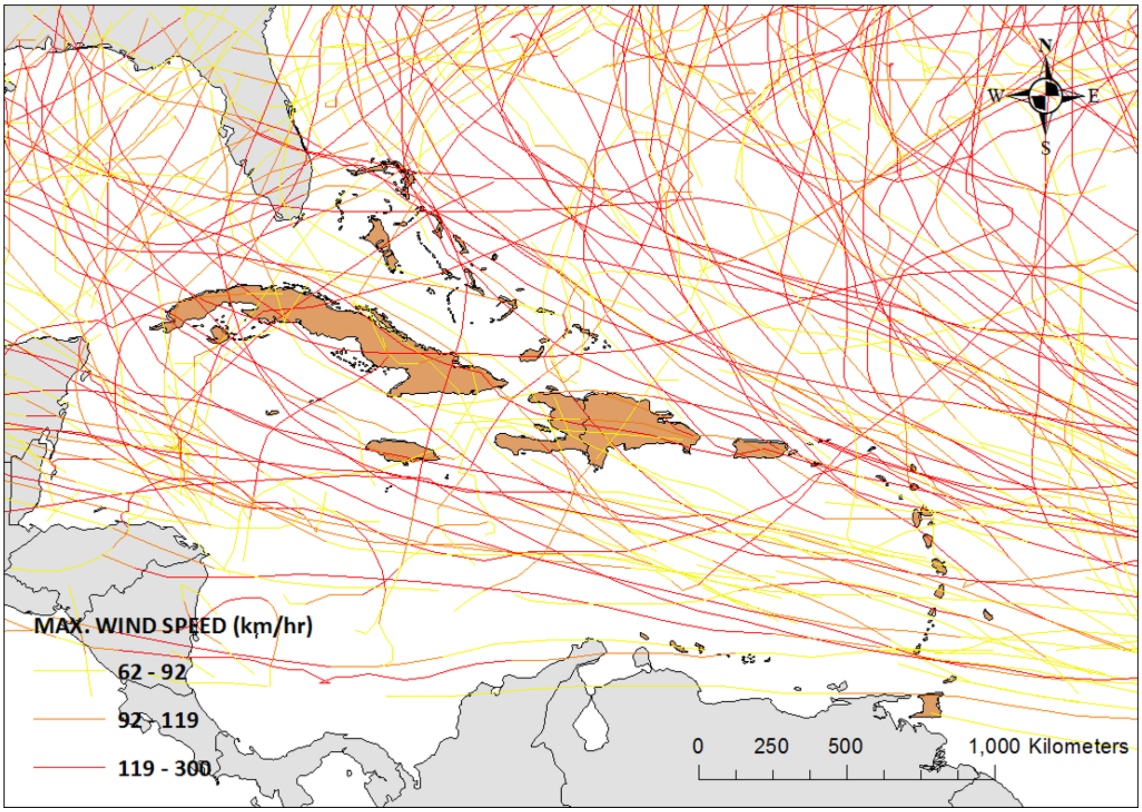
3.2 Hurricane Track Data

The modeling of hurricane destruction relies on hurricane best track data, which was obtained from the Atlantic Hurricane Database (HURDAT), maintained by the National Hurricane Center from the National Oceanic and Atmospheric Administration (NOAA). HURDAT provides six-hourly information on the location, maximum wind speed, and size of all cyclones in the North Atlantic Basin. For the purpose of this analysis, the data were interpolated to one-hourly positions and restricted to those storms that came within 500 km of any of the islands in the sample. Additionally, only storms that reached hurricane strength (wind speeds in excess of 119 km/h) at some point during their lifetime were included, since

[4] https://www.onecaribbean.org/

these are the ones likely to have caused any damage due to wind exposure. The tracks of the hurricanes that formed around the Caribbean between 2000-2013 are shown in Figure 1, where the red lines represent the storms that reached hurricane strength.

Figure 1: All tropical cyclone activity from 2000-2013



3.3 Island Level Economic Activity

Since there is no consistent monthly series of GDP across time and islands for the Caribbean, we proxy this with satellite-based monthly nightlight intensity data at the island level and within islands. Several papers show that nightlights exhibit a strong correlation with economic activity and can be used as a proxy in places where no other measurements are available (Henderson et al. (2012), Ghosh et al. (2013),(Mellander et al., 2015), and (Doll, 2008)). For the Caribbean monthly nightlights as a proxy for monthly economic activity has been used by Strobl (2019) and Ishizawa, Miranda, and Strobl (2017), and we followed their approach in this paper.

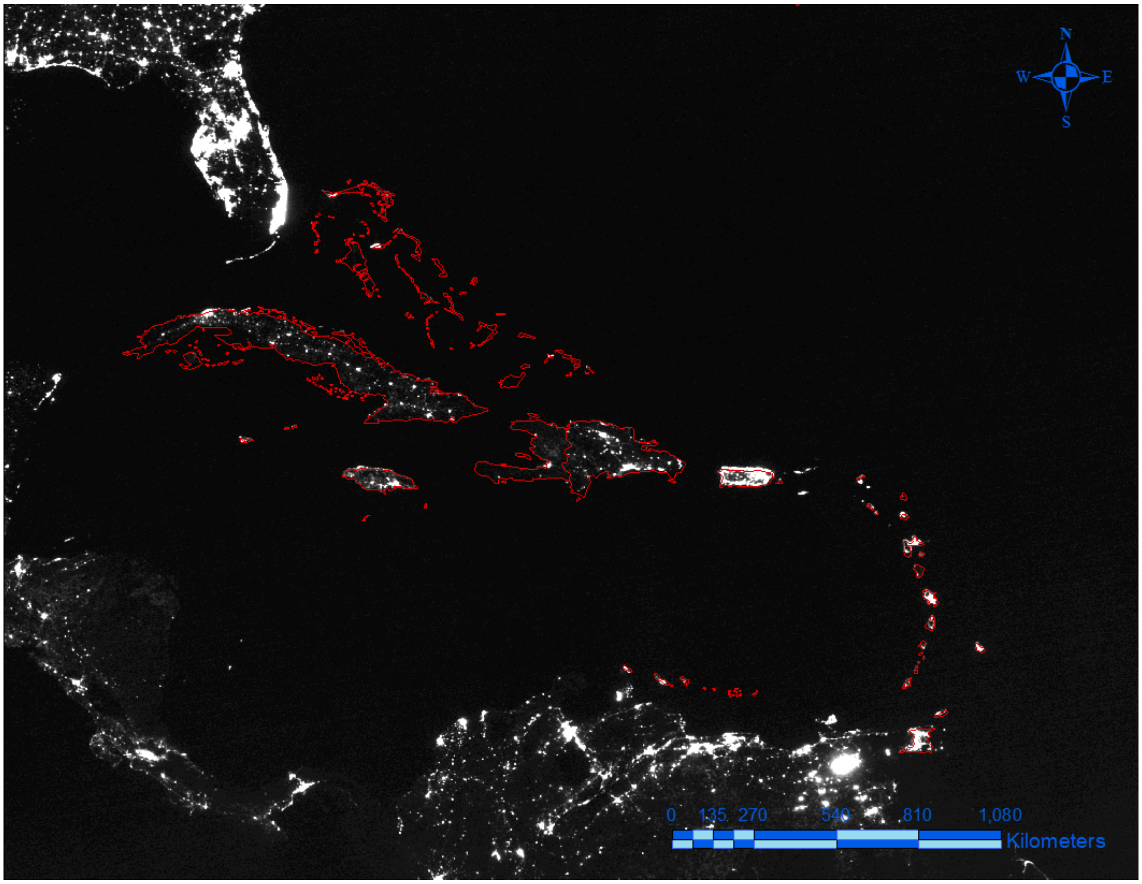
The data source used was the monthly nightlight data composites of the United States Air Force Defense Meteorological Satellite Program - Operational Linescan System (DMSP-OLS), available from 1992 until 2013, after which the satellite was discontinued. These satellites have a 101 minute sun-synchronous near-polar orbit at about 830 km above the surface of the earth, and provide global coverage twice per day at the same local time. They have a spatial resolution of approximately 1 km near the equator. To get clean nightlight luminosity, the raw data was first processed to remove pixels obscured by clouds and other sources of transient light. The data were then normalized to produce images with a nightlight intensity scale of 0 (no light) to 63 (maximum light). In order to calculate the averages from the stable monthly nightlight intensity and the number of cloud-free days, we used monthly composites from six NASA satellites namely F10, F12, F14, F15, F16, F18. These satellites have been used since 1992 when the DMSP-OLS began, and have been operating at different time periods with some overlapping years.[5] Because of these time overlaps, simple averages across the overlapping observations were calculated and unique monthly values for each pixel were derived. Ishizawa, Miranda, and Zhang (2017) provides results which confirm that using cloud weighted averages or the newest images produce qualitatively the same results. Figure 2 displays the Caribbean nightlights intensity for the year 2013, where the brightest spots depict centers of economic activity.

To provide a visual illustration of how nightlights are a reasonable proxy of economic activity in the Caribbean, Figure 3 shows a scatter plot of the relationship between the monthly real GDP of all 18 Caribbean islands under study and the sum of their nightlights intensity in 2013.[6] As can be seen, there is a clear positive correlation (albeit with some outliers), where the raw correlation was 0.87. This provides an indication that nightlights

[5]The operating periods for each satellite from 1992-2013 are: *F10* from 1992–1994, *F12* from 1994–1997, *F14* from 1997–2003, *F15* from 2000–2007, *F16* for 2004–2009, and *F18* for 2010-2013.

[6]The GDP value of each islands was retrieved for the year 2013 in USD from the Penn World Table except for Martinique, Puerto Rico, and the US Virgin Islands whose GDP values were obtained from national sources.

Figure 2: Nightlight intensity in the Caribbean in 2013



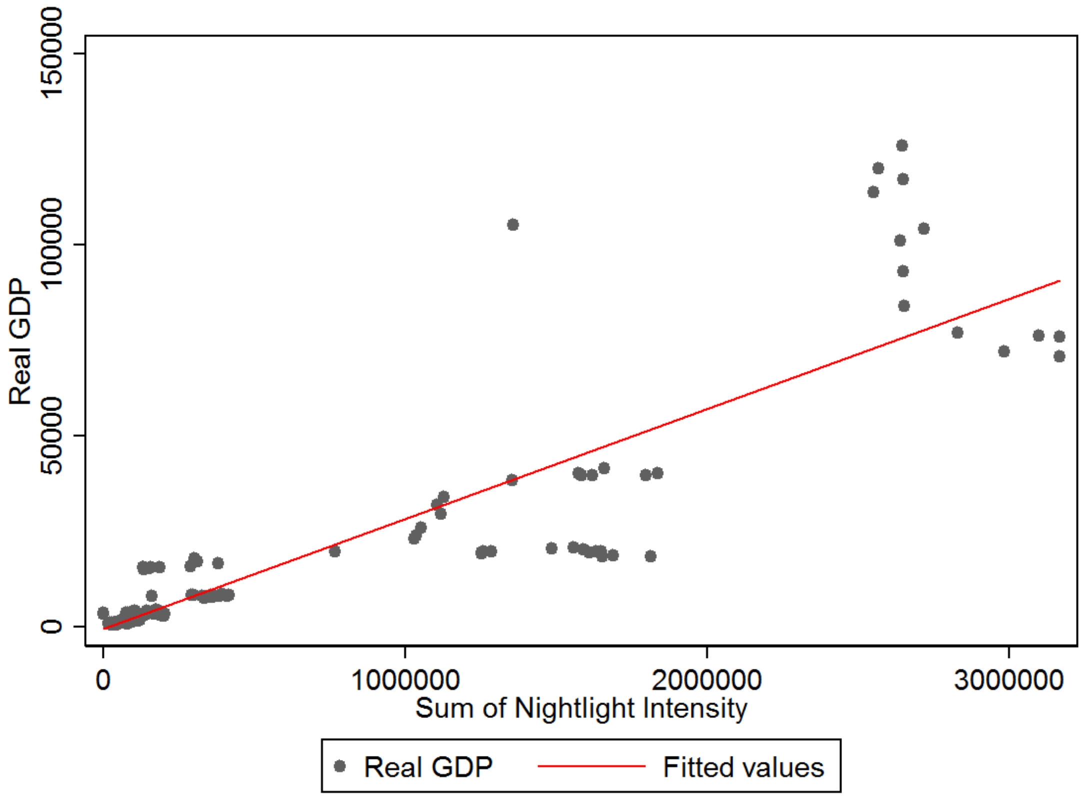
can serve as a reasonable proxy of economic activity when no other indicator of monthly economic activity is available.

3.4 Tourism Demand Indicators

While we are mainly interested in the impact of hurricanes on arrivals in our econometric analysis we also control for tourism demand. In order to construct such a measure of demand for tourism in the Caribbean as a source of income in the origin markets, we created a variable that takes account the three main origin markets, namely the United States, Canada, and Europe.[7] To this end we used real monthly GDP values (in 2013 chained US dollars) for these regions taken from their various national sources and their annual air arrival tourism

[7]We use the data of the countries in the Euro Area, where it should be noted that the number of member states has increased during our period of analysis from 11 to 17 countries.

Figure 3: Relationship between island level GDP and nightlights



shares in the Caribbean as provided by the CTO. To calculate tourism demand D for a particular island i the annual shares were linearly interpolated to monthly values at period $t-1$ rather than at t to avoid any endogenous effects in relation to hurricane strikes as follows:

$$D_{i,t} = \sum_{k=1}^{N} S_{k,i,t-1} \times GDP_{k,t}$$

where S is the share of each main market k in island i at time t. One should note that because of a lack of cruise arrivals by origin country we only captured demand in terms of air arrivals.

3.5 Tourism Expenditure

We used tourism expenditure data to put monetary valuations on the predictions that we derived from our econometric analysis. Although tourism expenditure data are available across the region, most islands do not distinguish spending between cruise and air arrivals in their reporting. This information was available for four islands (Barbados, Cayman Islands, Jamaica, and St. Kitts & Nevis). We used this data to calculate the average spending by tourist type. This calculation showed 106 US dollars per person per day for cruise ship tourists and 169 US dollars per person per day for tourists arriving by air.

4 Methodology

4.1 Hurricane Destruction Index

To construct the hurricane destruction index (*HDI*) we followed the methodology from Strobl (2019), which is based on Strobl (2012). This index used *ex-ante* data in conjunction with a physical wind field model rather than *ex-post* data, which can produce biased results (Strobl, 2012). The damage inflicted by hurricanes mainly depends on three related aspects: wind speed, storm surge, and flooding/excess rainfall. The latter two, in addition to being difficult to model, are highly correlated with wind speed (Emanuel, 2011). For this reason, most articles simplify the modelling, and rely on the assumption that wind speed is a strong proxy for the potential damage due to hurricanes.[8] In line with this, we also implemented this assumption.

4.1.1 Wind Field Model

The wind speed that a specific location will experience with the passing of a hurricane depends on the location of its position relative to the storm, and the movements, and features

[8] Emanuel (2011) provides a more detailed discussion about the relationship between wind speed, storm surge, and flooding/excess rainfall.

of the storm. To model the wind speed due to hurricanes, the Boose et al. (2004) version of the well-known wind field model from G. J. Holland (1980) was employed. This allowed us to calculate the wind speed v at any point j, for storm k at time t (see Strobl (2012) for details):

$$v_{j,k,t} = GF \left[V_{max,k,t} - S \left(1 - SIN(T_{j,k,t})\right) \frac{V_{h,k,t}}{2} \right] \left[\left(\frac{R_{max,k,t}}{R_{j,k,t}} \right)^{B_{jt}} exp \left(1 - \left[\frac{R_{max,k,t}}{R_{j,k,t}} \right]^{B_{jt}} \right) \right]^{\frac{1}{2}}, \tag{1}$$

where V_{max} is the maximum sustained wind velocity anywhere in the storm, T is the clockwise angle between the forward path of the hurricane and a radial line from the hurricane center to the pixel of interest j, V_h is the forward velocity of the hurricane, R_{max} is the radius of maximum winds, R is the radial distance from the center of the hurricane to point j, G the gust wind factor, and F, S, and B are the scaling factors for surface friction and asymmetry due to the forward motion of the storm, and the shape of the wind profile curve, respectively.

For the implementation of equation (1), the maximum wind speed V_{max}, was obtained from the HURDAT Best Track Data set mentioned above. V_h was calculated by following the movement path of the storm, and R and T were calculated by using the relative position between the eye of the hurricane and the point of interest j. In terms of the gust wind factor G, it was set equal to 1.5 following the results from Paulsen and Schroeder (2005). A value of 1 is assigned to S following G. J. Holland (1980). For the surface friction, factor F, the suggestions by Vickery et al. (2009) was followed: in open water the friction factor has a value of 0.7 but reduces by 14% on the coast and by 28% when the hurricane is 50 km inland. To account for these differences and following Elliott et al. (2015), a reduction factor was implemented that linearly decreases F as the location j moves inland. Finally, to obtain B and R_{max}, G. Holland (2008)'s approximation method and Xiao et al. (2009)'s parametric model were used.

4.1.2 Damage Function

Using the results from the wind speed model as inputs we adopted a damage function to model point specific damage. The damage function was based on Emanuel (2011), who noted that the potential damage due to hurricanes should vary with the cubic power of the wind speed experienced on physical grounds. He also noted that there is likely to be a wind threshold below which no substantial damage occurs. To incorporate these two features and to provide an index that varies between 0 and 1 capturing the fraction of damage, Emanuel (2011) proposes the following function:

$$HDI_{ijk} = \frac{v_{ijk}^3}{1 + v_{ijk}^3}, \tag{2}$$

where *HDI* is the fraction of damage and

$$v_{ijk} = \frac{MAX\left[(V_{ijk} - V_{thresh}), 0\right]}{V_{half} - V_{thresh}}, \tag{3}$$

where V_{ijk} is the maximum wind speed of storm j experienced at point of interest i in country k, V_{thresh} is the threshold below which no damage occurs, and V_{half} is the threshold at which half of the property is damaged. Based on Emanuel (2011) a value of 92 km (50 kts) for V_{thresh} and a value of 278 km (150kts) for V_{half} was used.

Lastly, to take into account the differences in exposure within islands, a weighted *HDI* was calculated to arrive at an island level index. This was done by calculating the share of nightlight intensity at each pixel relative to the island total at *t-1*, i.e. the month before a hurricane strikes. This was done to avoid endogeneity between the index and the hurricane shocks. These weighted shares were then used to generate the local nightlight intensity average *HDI* index as follows:

$$HDI_{jt} = \sum_{k \epsilon t} \sum_{i=1}^{N} w_{ikt-1} HDI_{ijk}$$

where w_{ikt-1} is the share of nightlights at point i in year *t-1* in island k.

4.2 The Econometric Model

Following Fomby et al. (2009) and Mejia (2014), the econometric model used in this article is a fixed-effects panel vector autoregression with an exogenous variable (VARX). The VAR structure enabled us to allow for lagged effects as well as feedback effects between the endogenous variables (air and cruise arrivals and tourism demand) from the exogenous shock (hurricane destruction). Including the island specific fixed effects in the specification ensured that the hurricane shock can be considered truly exogenous. More precisely, while the physical features of a particular storm and the pre-storm population exposure of an island can arguably be considered exogenous, it may be the case that when tourists consider their choices among islands and/or tourism agencies choose what island specific destination packages to offer they take into consideration the distribution of hurricane shocks. By controlling for island fixed effects we take into account these distributional features and are left with the random, i.e., exogenous, realizations of the actual hurricane occurrences, allowing us to interpret any effect causally.

Our panel data is an unbalanced panel and our basic VARX model is:

$$\mathrm{y_{i,t}} = \alpha_\mathrm{i} + \sum_{\mathrm{j=1}}^{\mathrm{p}} \Phi_{\mathrm{i,j}}\mathrm{y_{i,t-j}} + \sum_{\mathrm{k=0}}^{\mathrm{q}} \Theta_{\mathrm{i,j}}\mathrm{x_{i,t-j}} + \epsilon_{\mathrm{i,t}} \tag{4}$$

where the country index is $i = 1, 2, ..., N$, the time index for each country i is $t = 1, 2, ..., T_i$, $\mathrm{y_{i,t}}$ represents a 3×1 vector of endogenous variables, and $\mathrm{x_{i,t}}$ represents a 1×1 vector of the exogenous variable:

$$\mathbf{y_{i,t}} = \begin{bmatrix} \textit{Cruise Ship / Airplane}_{i,t} \\ \textit{Demand}_{i,t} \\ \textit{Nightlights}_{i,t} \end{bmatrix} \mathbf{x_{i,t}} = \begin{bmatrix} HDI_{i,t} \end{bmatrix} \tag{5}$$

In equation (4), the fixed-effects coefficient for each country is represented by α_i, which captures two things: (i) the unobserved time invariant heterogeneity among Caribbean countries, and (ii) the unobserved time specific factors common to all countries. To account for (ii), all endogenous and exogenous variables were time demeaned before estimation. The total number of observations is given by $T = \sum_{i=1}^{N} T_i$. In equation (4), it is assumed that the errors have a homogeneous structure $E(\epsilon_{i,s}\epsilon'_{i,t}) = \Omega$ for all i and t, where $\epsilon_{i,t}$ is the vector of errors of the system. Furthermore, it is assumed independence of errors within equations, $E(\epsilon_{i,s}\epsilon'_{j,t}) = 0$, $s \neq t$, and across equations, $E(\epsilon_{i,s}\epsilon'_{i,t}) = 0$, for any s and t where $i \neq j$. To be able to explore the possible difference in the impact that hurricanes have on cruise ship and airplane arrivals it is necessary to consider them as separate dependent variables as shown in Equation 5. They were both measured in their log form.

Given the dynamic nature of the VARX model, and as indicated by Nickell (1981), if the time series dimension of the panel (T_i) is small and fixed, then the within effect (α_i) or the least squares dummy estimator (LSDV) is inconsistent.[9] Given that the time dimension in our sample is limited and fixed (T=14), this could lead to an inconsistency which needs to be accounted for such that we can obtain a bias corrected LSDV. To achieve this, we used the bootstrapping algorithm from Fomby et al. (2009) and Mejia (2014), which is based on the work from Pesaran and Zhao (1999) and Everaert and Pozzi (2007). The steps taken to derive the bootstrapped bias corrected estimator (BSBC) are outlined in the Appendix.

4.2.1 Diagnostic Tests (Stationarity and Lag Structure)

To ensure the validity of the model, it is necessary to test for the stationarity of the variables in Equation 5. We employed the Im et al. (2003) panel unit root test (IPS) to help determine the order of integration that the variables need to take in order to be stationary.[10] The null hypothesis states that all the series have a unit root: $\mathrm{H}_0 : \phi_{\mathrm{i}} = 0$, for all i. Failure to reject the null hypothesis implies that a unit root exists, thus the series is non-stationary.

[9] This holds even if the number of countries (N) goes to infinity. However, as T_i grows, the bias decreases.
[10] This test is capable of running unbalanced panels thus appropriate for our data set.

The alternative hypothesis - implying stationarity - allows for individual unit roots (ϕ_i) to vary across countries in the following manner: $\mathrm{H}_1 : \phi_\mathrm{i} < 0$, for at least one country i.

In addition, to correctly specifying the VARX model it is important to find the optimal number of lags to be included for each variable. To choose these for the benchmark model (BSBC estimator), the following two information criteria were considered: (i) the Aikaike's information criterion (AIC), and (ii) the Schwarz's Bayesian information criterion (SBC).

5 Results

5.1 Summary Statistics

Our sample consists of a panel of monthly observations of 18 Caribbean SIDS covering the period 2000-2013, where the end of the sample period was constrained by the availability of the DMSP nightlight data used to measure local population exposure. The total number of cruise ship and airplane arrivals in each island during the 2000-2013 period is shown in Table 1 below. Here, it can be seen that The Bahamas was the most popular island for cruise ship travellers with over 41.7 million visitors, while Trinidad and Tobago saw the smallest number of visitors. On the other hand, tourists arriving by airplane has some slightly different preferences with the Dominican Republic getting the largest share with almost 45 million visitors and St Kitts and Nevis getting the least amount of arrivals. On average a country received a larger number of cruise than plane tourists (10 million versus 9.3 million). The market share of cruise versus air tourists in each island is shown in the last column of Table 1). In Dominica cruise ship tourists accounted for over 80% of visitors, while in the Dominican Republic only 9% of the tourists came by cruise ship. Other popular islands - in relative terms - for cruise ship tourists were the Netherlands Antilles (77%) and St Kitts and Nevis (70%). The average share of cruise ship tourists is slightly higher at 55% per island.

Looking at the summary statistics of all the variables in Table 2, the average monthly

Table 1: Total cruise ship and airplane arrivals 2000-2013 (in millions)

	Islands	Cruise ship	Airplane	Total	Share Cruise
1	Antigua and Barbuda	7.017	3.047	10.064	0.697
2	Aruba	7.875	10.623	18.498	0.426
3	Bahamas	41.678	18.404	60.082	0.694
4	Barbados	8.114	7.352	15.466	0.525
5	Cayman Islands	13.680	10.373	24.053	0.569
6	Dominica	4.347	0.996	5.343	0.814
7	Dominican Republic	4.609	44.773	49.382	0.093
8	Grenada	3.311	1.660	4.971	0.666
9	Haiti	3.486	1.562	5.048	0.691
10	Jamaica	14.255	20.670	34.925	0.408
11	Martinique	1.848	6.345	8.193	0.226
12	Netherlands Antilles	16.385	4.992	21.377	0.766
13	Puerto Rico	16.856	17.756	34.612	0.487
14	St Kitts and Nevis	2.255	0.981	3.235	0.697
15	St Lucia	7.205	3.900	11.105	0.649
16	St Vincent and the Grenadines	1.319	1.078	2.398	0.550
17	Trinidad and Tobago	0.830	4.545	5.375	0.154
18	US Virgin Islands	24.942	8.705	33.647	0.741
	Total	180.011	167.764	347.775	9.852
	Average	10.001	9.320	19.321	0.547

arrivals of cruise ship and airplane tourists was in excess of 60 thousand visitors per month. The maximum number of tourists arriving by airplane was to the Dominican Republic in March of 2013, and for cruise ships was to the Bahamas in December of 2013. The lowest values in our sample for cruise and air arrivals were the Cayman Islands during October of 2004, when only 1,968 visitors came by airplane and 1,766 by cruise. These low numbers coincide with Hurricane Ivan, which caused large destruction.

Regarding nightlights, Table 2 provides the statistics for the mean of all non-zero nightlight values. These numbers suggest that the average nightlight intensity in the Caribbean was 20.36, while the maximum value in the sample was 61.28, which was recorded in the Netherlands Antilles during the month of May of 2002. The large standard deviation indicates large differences in the light radiance measurements across the islands.

Table 2: Summary Statistics

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Cruise ships	2,682	67,118	76,054	0	534,534
Airplanes	2,682	62,552	76,354	1,968	500,712
Demand	2,682	9,765	3,401	1,766	16,145
Nightlights	2,682	20.36	12.6	3.6	61.28
HDI	2,682	0.007	0.056	0	0.884
$HDI \neq 0$	164	0.118	0.195	0	0.884

Finally, the summary statistics of the hurricane destruction index (Table 2), suggest that the range of destruction varied greatly between the minimum values of zero (no destruction) and the maximum value of 0.884 (recorded from Hurricane Ivan in the Cayman Islands in October of 2004). The mean of all observations was 0.007 with a standard deviation of 0.056. If only the observations when a hurricane occurred were accounted for (all non-zero values) there were only 164 observations with a mean of 0.118 and a standard deviation of 0.195. To illustrate how the degree of destruction varied among islands, Figure 4 shows the distribution of the average monthly values. Here, it can be seen that the amount of destruction that the islands experienced during the sample period varied substantially. Also, the islands that suffered the largest damages were the Cayman Islands, Jamaica, and the Bahamas.

5.2 Stationarity and Lag Structure

The results from the stationarity test are summarized in Table 3. They suggest that Demand is a non-stationary variable, but when first-differenced it becomes stationary. All other variables are stationary.

The lag structure results were based on the AIC and SBC. These results for the cruise ship and airplane variables are presented in Table 4, where p and q indicate the number of lags for the endogenous and exogenous variables, respectively. The statistics show that while the SBC suggests a lag structure of p=q=*5*, the AIC suggests p=q=*12*. However, the AIC criteria consistently prefers the models with larger lag structures, suggesting that if more

Figure 4: Distribution of monthly average *HDI*

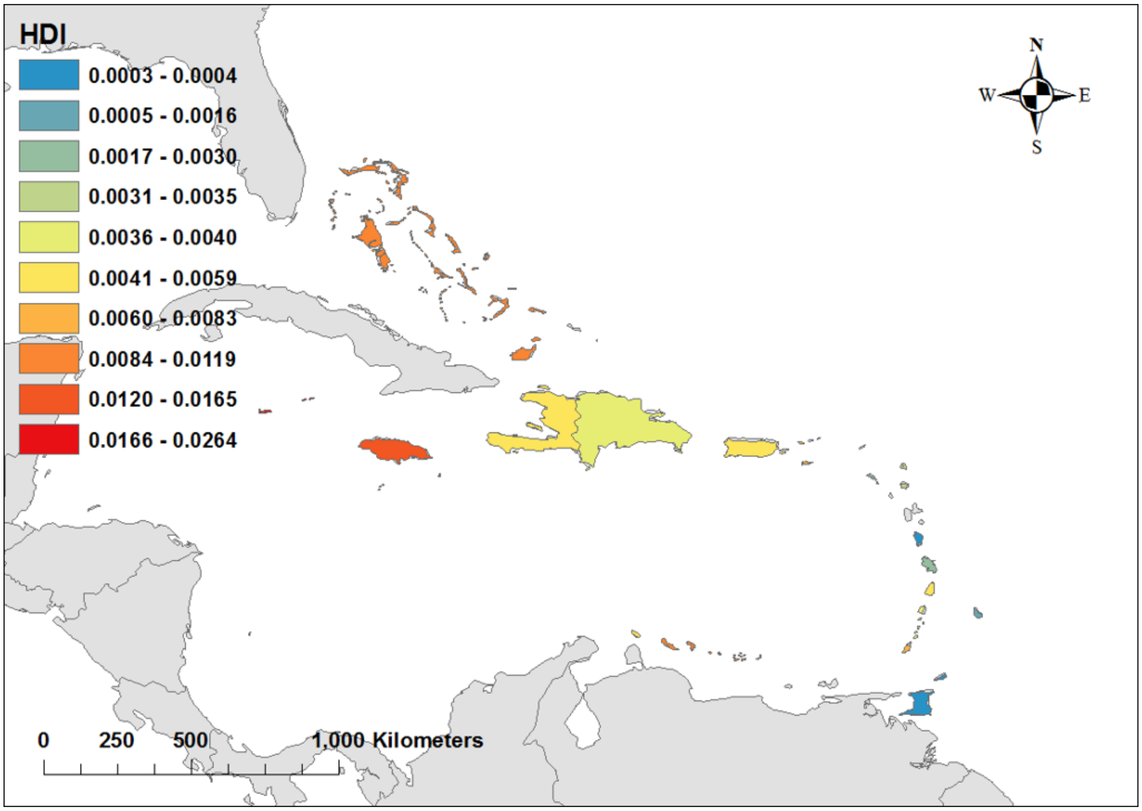


Table 3: IPS panel unit-root test

Variables	IPS panel unit-root pest		Order of integration
	test-stat	p-value	
Cruise Ships	-17.6711	0.0000	I(0)
ΔCruise Ships	-	-	
Airplanes	-22.5707	0.0000	I(0)
ΔAirplanes	-	-	
Demand	1.3924	0.9181	I(1)
ΔDemand	-6.5654	0.0000	
Nightlights	-23.8927	0.0000	I(1)
ΔNightlights	-31.5218	0.0000	

lags were to be included, the AIC would continue to select the larger model. This observation is consistent with the literature, which says that the AIC is generally more likely to choose larger models (Kuha, 2004). Based on this and on the overall time span of our data, a lag length of six was chosen. This lag structure should be rich enough to capture the dynamic effect of the shock.

Table 4: Lag selection criteria

	Variables			
	Cruise ship		Airplane	
Number of lags	AIC	SBC	AIC	SBC
p=q=4	16.413	16.525	13.241	13.353
p=q=5	16.351	**16.489**	13.208	**13.347**
p=q=6	16.339	16.503	13.196	13.361
p=q=7	16.328	16.519	13.182	13.373
p=q=8	16.315	16.532	13.176	13.394
p=q=9	16.308	16.552	13.175	13.419
p=q=10	16.292	16.562	13.167	13.437
p=q=11	16.251	16.548	13.151	13.448
p=q=12	**16.225**	16.548	**13.143**	13.466

Note: The lags with the minimum value are preferred and highlighted.

5.3 Benchmark Results

The main focus of this paper is to investigate the dynamic effects and adjustment path of tourist arrivals after a hurricane strike in the Caribbean. To this end, the mean impulse responses and mean cumulative responses obtained from the VARX analysis was used. The coefficients of the mean responses provide the specific effects of hurricanes during the actual month of the strike as well as the months thereafter. These coefficients are reported in Table 5, where the first period (month 0) represents the month when a hurricane occurred, and the last period reported is month 6 (the effects after month 6 are either close to 0 or not statistically significant and thus not reported). The cumulative effect is also included in the last row of Table 5.[11] Additionally, the mean response coefficients and their corresponding 10% confidence intervals are graphically depicted in Figure 5 with time horizons spanning

[11]It was calculated by summing all the individual coefficients from month 0 to 6.

up to month 16.[12] The graphs in Figure 5 are organized as follows: the first and second column represent the airplane and cruise ship arrivals in that order, the upper half shows the mean impulse responses, and the lower half shows the mean cumulative responses.

The results from Table 5 and Figure 5 (top plane) show that hurricanes have an immediate and significant negative impact on the number of tourist arrivals in the month of a strike and 1 month after on cruise ship (a drop of 2.33 and 1.21 percentage points) and airplane (a drop of 0.57 and 0.27 percentage points) arrivals. However, cruise ship arrivals are significantly harder hit, with an impact about 4 times that of airplane arrivals. If averaged, the impact on both types of arrivals equals to a drop of 1.10 percentage points. Granvorka and Strobl (2013) similarly found that hurricanes reduced arrivals to the Caribbean in the month of a strike by 1.76 percentage points.

In the first 6 months following a hurricane, the dynamics of adjustment suggest that arrival numbers recovered. Table 5 and Figure 5 show that both responses turned positive in month 3, although only airplanes was statistically significant. The cruise ship recovery was somewhat weaker, with a shorter period of positive delayed effects (month 3 to 7 and not statistically significant).

The bottom panel of Figure 5 shows the cumulative effects of HDI, which is just the sum of the estimated coefficients along with the estimated confidence interval of these sums. Accordingly, this suggests that the strong recovery of airplane arrivals was sufficient to induce a net positive effect of around 2 percentage points of total arrivals into the region by the sixth month after a storm. On the contrary, the large contemporaneous impact and the weaker and statistically insignificant recovery of cruise ship arrivals caused the cumulative net effect to remain negative up until the fifth month, after which it became insignificant.

Besides the BSBC estimator results from the benchmark model, the results from the LSDV estimator for fixed-effects models were also calculated as a robustness check. When comparing the results from the BSCB estimator with those from the LSDV estimator, the

[12] The confidence bands were constructed using a Monte Carlo procedure. They were also used to determine the statistical significance of the coefficients in Table 5.

Figure 5: Mean responses of cruise ship and airplane arrivals to hurricane shocks

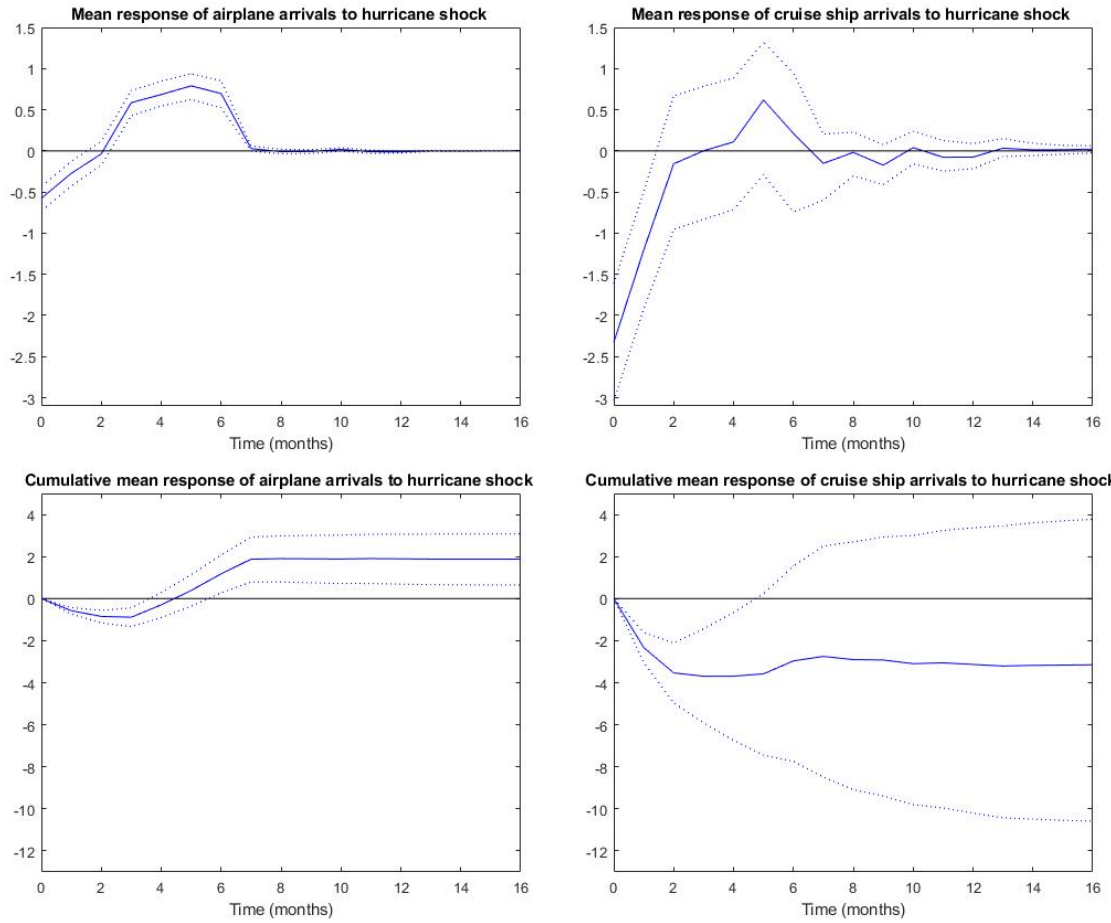


Table 5: Mean responses of cruise ship and airplane arrivals to hurricane shocks

Month	Cruise Ship	Airplane
0 (Impact Effect)	-2.328 **	-0.576 **
1	-1.205 **	-0.272 **
2	-0.157	-0.037
3	0.001	0.587 **
4	0.109	0.685 **
5	0.619	0.790 **
6	0.212	0.697 **
Cumulative Effect	-2.750	1.874 **

Note: 5% and 10% significance levels are represented by * and **, respectively results were very similar in sign, significance and size.

5.4 Economic impact

To translate our results into monetary impacts we used the means of the number of tourist arrivals, the spending of tourist per day translated into monthly spending, the estimated coefficients from the panel VARX model, and two different values of the hurricane destruction index, namely its non-zero mean and the maximum observed value in our data.

When we used the mean *HDI* value of all the months when a hurricane actually occurred, the revenue losses during the month of a strike was USD 1.95 million from cruise ship tourists and USD 0.72 million from airplane tourists. However, if the cumulative economic impact is considered, the results differ substantially. For instance, 6 months after a hurricane occurred, revenue losses from cruise ship passengers amounted to USD 2.31 million, whereas revenues from airplane tourists were positive and totalled USD 2.33 million. This stems from the fact that the net impact of airplane arrivals was positive, while cruise ship arrivals was negative. Furthermore, because airplane passengers have a higher average spend, the difference was exacerbated. Next, we considered the impact of the strongest hurricane in the sample. In this case, the drop in cruise ship tourists caused revenue losses of USD 14.65 million during the month of a strike, and USD 17.3 million 6 months after. Meanwhile, the revenue losses from airplane tourists was USD 5.38 million in month $t = 0$, but the net impact 6 months after was positive and amounted to USD 17.49 million. Thus, the net impact of hurricanes on tourist arrivals is roughly zero. Table 6 provides a monthly and cumulative overview of the revenue and arrival impact.

Table 6: Economic impact of hurricanes

	Cruise ship arrivals			
	$Mean_{HDI \neq 0}$ (0.118)		Max_{HDI} (0.884)	
Month	No. Arrivals	$USDm	No. Arrivals	$USDm
0	-18,436	-1.955	-138,111	-14.647
1	-9,547	-1.012	-71,519	-7.585
2	-1,244	-0.132	-9,321	-0.989
3	8	0.001	63	0.007
4	864	0.092	6,470	0.686
5	4,900	0.52	36,711	3.893
6	1,677	0.178	12,561	1.332
CE	-21,777	-2.31	-163,146	-17.302
	Airplane arrivals			
0	-4,252	-0.718	-31,854	-5.377
1	-2,007	-0.339	-15,034	-2.538
2	-270	-0.046	-2,025	-0.342
3	4,330	0.731	32,437	5.475
4	5,053	0.853	37,858	6.39
5	5,832	0.985	43,694	7.376
6	5,144	0.868	38,535	6.505
CE	13,831	2.335	103,612	17.49

6 Discussion

The findings of this paper demonstrate that there was an initial and significant negative impact of hurricanes (in the month of a strike and up to 1 month thereafter) on air and cruise arrivals in the Caribbean. The results also suggest that the magnitude of the negative effect was different for cruise versus air arrivals. Cruise ship passengers were about 4 times more adversely affected by hurricanes than air passengers. Additionally, the subsequent recovery trajectories differed. While airplane arrivals quickly rebounded and showed a net positive effect from the third to the sixth month following a hurricane event, the number of cruise ship arrivals did not experience a similar recovery, and results in an overall zero net effect on total arrivals. This may be due to several factors such as flexibility of air travel re-scheduling, possible destination changes from cruise operators, and promotions and discounts aimed at different tourist segments.

The fact that different segments of tourists showed different adjustment effects points to the importance of being able to distinguish between different groups of tourists. These differences can provide an insight into how local authorities and industry leaders can approach cruise tourists and airplane tourists in the Caribbean. Firstly, it seems as if the region's ex-post hurricane efforts at attracting airplane tourists are working. Secondly, it shows that countries should potentially try to incentivize cruise ship companies and passengers to continue to visit at ex-ante levels following a hurricane event. These results are noteworthy since the effect that natural disasters and more generally negative shocks have on different types of tourists has been sparsely studied in the literature before. Moreover, the literature suggests that disaster-related tourism could actually lead to an increase in certain types of tourists, such as humanitarian tourists and persons visiting friends and family who have been victims of calamitous events (Rosselló et al. (2020)). Thus, more research on negative events in the tourism sector and the impact on different types of tourists would further shed light on this issue.

The relatively large difference in the degree of the initial impact between cruise ship and airplane arrivals during the month of a strike and 1 month after may be explained by the fact that when a hurricane hits the region, cruise ships simply re-route and change their itinerary to avoid affected areas. This is done by either skipping a scheduled stop, which results in staying an extra day at sea, or by substituting the skipped port/island with another one (CC (2020)). By doing so, cruise ship passengers miss one or more of their destinations, and leave the skipped port/islands with no chance to attract these missed tourists in the immediate future. Moreover, cruise ship tourists mostly pay for the on-board experience and spend a limited amount of time (a day or even a few hours) at the stops. Hence, there is no major incentive to book another cruise trip just to visit the missed destination.

On the other hand, although also negatively impacted, airplane arrivals appear to absorb the hurricane shock in a more resilient manner. A possible explanation for this might be the relative flexibility of airlines compared to that of cruise ships when dealing with a hurricane. For instance, if a hurricane disrupts a planned flight, airlines generally allow (or are forced to by consumer laws) their passengers to reschedule their trip with no penalties, no fees, and no changes in fares within a relatively short space of time ((Perkins, 2016)). The rescheduling usually leads to a travel postponement of only a couple of days ((Perkins, 2016) and (Glusac, 2019)) rather than complete cancellation of the trip.

The recovery in the number of tourist arrivals up to 6 months after a hurricane shock was positive and significant for airplane arrivals only. A possible explanation for the discrepancies between cruise ship and airplane travellers might be the price incentives and discounts offered by airlines and hotels following a hurricane. For instance, after a hurricane occurs, airlines and hotels usually offer discounted prices to attract visitors to try to recover the drop in demand (Pace (2018)). Meanwhile, cruise ship companies do not offer additional discounts ex-post a hurricane because cruise ship prices are already at a discounted price during the hurricane season (CC (2020)). Furthermore, cruise ship tourists do not book hotel nights at their stops because they already paid for their cruise ship rooms, thus the discounted hotel prices do not offer any further incentives for them.

The net monetary implication of a hurricane on tourism when combining both tourist segments comes out at approximately zero. In other words, there was a shift in the tourism revenue flow after a hurricane, but the aggregated tourism revenue stayed constant. However, it is important to point out that this finding heavily relied on rough tourist expenditure data, which is hard to obtain and may significantly vary from island to island. Additionally, it must be noted that our revenue figures do not consider the costs incurred through the various promotions and discounts offered to visitors, as well as the added costs of post-disaster clean-up and repair. Preferably, one would want to know the profit per tourist. After all, these are net spend (revenue) numbers, meaning that profits might be significantly reduced due to costs associated with trying to attract more tourists through repairs and discounts.

This paper provides empirical results that hurricanes unfavourably impact visitor arrivals in Caribbean SIDS, which has significant managerial implications. The Caribbean is disaster prone as it is highly susceptible to frequent and intensifying hurricane risk exacerbated by climate change (CCRIF (2010)). The Caribbean is also the most tourism dependent region globally for income, employment, and foreign exchange (Mooney and Zegarra (2020)). The fall in arrivals after a hurricane strike is likely due to damages to infrastructure including air and sea ports, amenities, hotels and other accommodations and tourist attractions, along with a general increase in economic and social disruption and safety and security concerns, all of which reduce the destination's ability to accommodate tourists and its attractiveness, at least in the short-term (Rosselló et al. (2020), Becken et al. (2015) and Sönmez et al. (1999)). As such, it is imperative that the Caribbean place special emphasis on tourism disaster management and planning and mitigation to buffer against destructive hurricane events and their accompanying reductions in tourist arrivals.

According to the literature tourism disaster management often involves a reactive approach to disaster response and recovery efforts rather than a proactive approach that involves strategic planning and prevention approaches to crisis and disaster management in the sector (Ritchie (2008)). There is also a lack of disaster management in tourism and appropriate frameworks to increase tourism disaster management at the destination level (Hystad and Keller (2008)). Furthermore, there is limited research in understanding tourism reduction and readiness efforts and barriers in tourism disaster planning to ensure more effective planning and management are undertaken when catastrophic events occur (Ritchie (2008)).

In the Caribbean a regional Disaster Risk Management Strategy and Plan of Action for tourism was developed between 2007 to 2010 through the collective action of regional as well as national stakeholders to address mitigation, preparedness, response, and recovery. The plan aims to enhance and supplement reactive measures with more proactive pre-event activities aimed at reducing the impact of potential hazards and plan for effective recovery (CDEMA2009). It is also characterized by the recognition of the need to mainstream disaster risk management not only in tourism but all sectors of society. There is however no study on the effectiveness of preparedness, responses, and recovery methods in the Caribbean tourism industry. Future research should therefore be placed on understanding the level of planning and preparedness for disaster events in the tourism sector and the development of effective reduction and readiness strategies linked to planning and prevention strategies.

The empirical results of this paper also suggest that natural disasters present challenges for tourism managers as they have to deal with an unexpected fall in tourism demand. The damage from hurricanes in Caribbean SIDS leads to reductions in both air and cruise arrivals. Tourism managers in these destinations should focus on the recovery of essential infrastructure and business capability in order to restore tourism demand as soon as possible. Proactive planning by tourism stakeholders around business continuity, business support networks, and recovery assistance programs, could accelerate this effort, where response and recovery is often led by individuals with a strong commitment to, and engagement with, the affected community Rosselló et al. (2020). Marketing activities also have to be designed with care to attract the right types of visitors at the right time taking into account tourism capacity, since natural disasters can attract certain types of visors and encourage risky behaviour. Marketing campaigns implemented by businesses, local tourist organizers and national tourism bureaus should align their messaging following a natural disaster to attract the right visitors at the right time.

7 Conclusion

In this study we contribute to the scant literature on the impact of catastrophic events on international tourist arrivals. More specifically, we investigated the impact of hurricanes on tourism in the Caribbean, distinguishing between the effect on cruise versus air arrival tourists. To this end we compiled a monthly data set of tourist arrivals, hurricane damages, economic activity, and regional tourism demand, and employed a panel Vector Autoregression Model where the hurricane effect was modeled as an exogenous shock to the system. Our results show that there was an immediate impact on both types of tourists, lasting a month, but the size of the reduction of tourists was substantially larger for air arrivals. However, air arrivals more than recovered a few months later, implying that the net overall effect on tourism expenditure was roughly zero. Our results have potentially important implications for disaster mitigation policies for the tourism industry in that they provide a first view on the quantitative impact, including monetary costs, of different segments of the tourism market.

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