Economic Working Papers

UNIVERSITY OF THE WEST INDIES

Cave Hill, Barbados • Mona, Jamaica • St. Augustine, Trinidad and Tobago

NO. 3, MAR 2016

Look What The Hurricanes Just Blew In: Analyzing the Impact of the Storm on Criminal Activities

By NEKEISHA SPENCER*

There is no obvious consensus in the literature on the relationship between crime and natural disasters. Specifically, studies have presented positive, negative and, no impact relationships using either a small number or an aggregation of criminal offences. This present study fills a gap in the literature by using multiple hurricanes to explore the economic impact of hurricanes on criminal activities from 1976-2012. I find that hurricanes increases crime per capita in counties that are directly hit, while neighboring counties experience a decline. This study has implications for the allocation of resources and national security in the face of natural disasters.

JEL:

Keywords: crime, hurricane, difference-in-difference

* Department of Economics, University of the West Indies at Mona, Jamaica. The author of this paper thanks Professors Polachek, Flores-Lagunes, and Carrion-Flores at Binghamton University for their useful comments throughout the development of this paper. Papers are peer-reviewed by UWI Working Paper Series editorial board members.

Florida is inherently vulnerable to natural disasters primarily because of its location. It is located in the southeastern region of the United States which faces the ongoing threat of hurricanes with a high probability. The devastation brought about by hurricanes has been noted in the number deaths, losses of property, and increases in the prices of agricultural produce. Blake et al.'s (2011) compilation of the deadliest, costliest, and most intense hurricanes in the United States, showed Florida being ranked number two for having 2,500 deaths using historical data since 1851. It is ranked number one along with two other states for experiencing losses amounting to US$108 billion in August 2005 from hurricane Katrina. Florida is also ranked number four for damages totaling over $21 billion after being struck by Wilma, a category three hurricane that made landfall in October 2005.

From the growing literature, hurricanes not only result in deaths and significant monetary losses, but are commonly associated with changes in human behavior. To this end, many empirical studies try to draw a connection between weather disturbances and criminal activities. With hurricanes being a regular occurrence, there is an increase in the number of studies looking at the impact of these disasters on crime outcomes (including Zahran et al. 2009; Leitner and Helbich 2010; Varano et al. 2010). Much attention has been given to destructive hurricanes such Andrew, Katrina, and Rita, and their impact in cities such as Houston, New Orleans, and Louisiana in the United States. The literature presents mixed results as it relates to the relationship between criminal activities and natural disasters. Studies found positive impacts (Frailing and Harper 2007; Leitner and Helbich, 2010; Thornton and Voigt 2007; Hussey et al. 2011), negative impacts (Bailey 2009; Zahran et al. 2009; Varano et al. 2010), and no impact (Cromwell et al. 1995; Bass 2008; Leitner and Helbich 2010). Among the existing studies, quite a number focused on at most two hurricanes, specific location(s), or simple descriptive analyses (Bass 2008; Bailey 2009; Thornton and Voigt 2007; Leitner and Helbich 2010; Walker et al. 2012). On the other hand, Zahran et al. (2009) looked at the effect of multiple disasters on crime in Florida for the period 1991 to 2005.

Like Zahran et al. (2009), this study uses all sixty seven counties in Florida, but only with respect to a single type of natural disaster, namely hurricanes. This study departs from existing research by using a longer time period, 1976 to 2012, over which Florida experienced devastating effects from multiple hurricanes. It also applies the relatively new generalized difference-in-difference technique to investigate the impact of hurricanes on seven major crime outcomes. These outcomes are: aggravated assault, burglary, forcible rape, larceny, motor vehicle theft, murder, and robbery. Looking at individual crime outcomes stands in contrast to Zahran et al. (2009) who used aggregated crime data (indexed crimes) to draw conclusions about the impact of disasters on crime in Florida. The benefit of using disaggregated data is to help citizens and policymakers understand the likely effect of hurricanes on different types of crime. This allows for proper measures to be implemented, and resources to be allocated in order to deal with each type of criminal activities. Aggregation makes it difficult to determine which type of crime needs to be targeted at a higher level so as to maintain stability in the economy. The analytic technique used here allows one to capture two main effects: direct and neighboring. The former effect represents the counties that were in the immediate path of the hurricanes, and the latter captures counties that were adjacent to these areas. In addition, the effects of both strong and weak hurricanes are disaggregated to isolate the effects based on the intensity of these storms.

This study is theoretically grounded on the work of previous authors who have put forward the possible relationships between crime, weather, sudden events, vulnerability and changes in behavior. Cohen and Felson (1979) on the routine activities viewpoint, postulated that crime occurs when a vulnerable situation exists, a lack of protection, and the existence of those wanting to cause harm; they argued that the latter results from changes in the structure of routine activities. Thus, a natural disaster changes routine activities, increasing the probability that criminals will identify those who are vulnerable and without protection (Zahran et al. 2009). From the rational choice and situational perspectives, Clarke and Cornish (1985) pointed out that a sudden crisis, event or condition are key elements that criminals take into account when deciding to commit a crime. Biological theories are also clear on how changes in weather can affect individuals' behavior, whether induced by high stressed events or by personal preferences for certain weather conditions (Moos, 1976). Psychological theories also support the relationship between crime and weather (Baron 1978; Bell 1992; Anderson and Anderson 1998); however, their focus has been on the individual itself rather than on the occurrence of an event or crisis, such as aggression arising from changes in temperature. Thus, the many crime studies tend to lean towards forming their theoretical bases on the former theories than on the latter ones. In addition, from the theoretical viewpoint of social disorganization, natural disasters can exacerbate the social conditions (i.e., instability and low socioeconomic status) causing disorganization and crime (Davila et al. 2005; Zahran et al. 2009). Moreover, these disasters can disrupt social unity and weaken the response to control crime (Taylor 1989; Berkowitz 1993; Curtis et al. 2000).

Furthermore, Becker (1968) pointed out that committing criminal offences is a function of the costs and benefits involved. Hence, from an economic perspective, an individual will commit a crime if the expected benefit is greater than the expected costs. As a result, if the likelihood of being caught is high, then committing an offence will likely decrease because of the high costs involved and vice versa (Horrocks and Menclova 2011). Unexpected weather events or crises tend to create vulnerable situations; thus, if the other two elements of Cohen and Felson's (1979) theory exists, then criminals comparing the cost and benefit of committing a crime, will realize greater benefits since the probability of being caught is low.

The foregoing theories make it clear that weather can affect criminal behavior. Hurricanes are events that tend to generate situations where protection is limited due a lack of security resources (Thornton and Voight 2007; Hussey et al. 2011), and which attract criminals. Thus, this study hypothesizes that hurricanes will positively impact criminal activities, and that stronger storms will have a greater impact than weaker storms.

The rest of this paper is organized as follows. In the next section, the literature on hurricanes and crimes is presented along with how hurricane shocks are modelled. The data, model specification, diagnostic tests are then discussed. A discussion of the estimated results and robustness checks follow. Lastly, the conclusion is presented with some policy implications.

I. Literature Review

The regularity of hurricane occurrences has drawn more researchers to study the impacts of these disasters on various aspects of life. In the literature, increasing attention has been given to the impact that hurricanes have on criminal activities. Some studies focus on a variety of criminal activities, while others key in on a single activity. Looting, which is the taking of merchandise by force, and rape have been the focus of a number of researchers. Quarantelli and Dynes (1970), and Wenger and Friedman (1986) contended that looting due to the occurrence of a natural disaster is simply a myth that is widely publicized by the media. So individuals might not necessarily loot even if they had the opportunity to do so when a disaster strikes. Ali (2013) emphasized that, at times, media myths distort the picture of areas that are affected by disasters. Nevertheless, he argued that these myths have some truth to them and so should not be heavily criticized. Other researchers held a different viewpoint on looting. They believed that there is no myth to such activity. Using burglary as a proxy for looting in New Orleans, Louisiana, Frailing and Harper (2007) found 15.4 and 402.9 percent increases in the burglary rate due to the passages of hurricanes Betsy and Katrina in 1965 and 2005 respectively. Manusinghe (2007) also emphasized the widespread looting that overwhelmed residents when hurricane Katrina struck New Orleans. In addition, for hurricane Katrina, some women who were unable to evacuate as well as those who came to assist in the recovery programme became rape victims (Thornton and Voigt 2007).

Several studies have given their attention to more than one types of crime. Leitner and Helbich's (2010) spatial-temporal analysis found significant increases in burglaries and motor vehicle theft in Houston, Texas. These short-term increases related to Hurricane Rita which struck in September 2005. The authors pointed out that the mandatory evacuation order given before Rita made landfall was not observed by all, and so those remaining behind raided the homes of evacuees. In contrast, evacuation was not compulsory for hurricane Katrina, thus, Leitner and Helbich found no impact on crime. In addition, for Houston, Hussey et al. (2011) found remarkable increases in murder, aggravated assault, illegal possession of weapons, and arson. Hussey et al. also noted increases in murder, robbery and motor vehicle theft for New Orleans due to hurricane Katrina. North Carolina was not exempted from changes in crime after hurricane Hugo. The state experienced temporary increases in domestic violence and burglary (LeBeau 2002). Phoenix, Arizona saw significant increases in murder after the passing of hurricane Katrina due population displacement in New Orleans (Varano et al. 2010).

Research has not been limited to studying the impact of natural disasters on a small scale – that is, on specific cities such as New Orleans and Houston. Authors such as Zahran et al. (2009) and Leitner and Helbich (2011) have made large scale studies their focus. Research findings on Florida indicated significant decreases in index, property and violent crimes, while significant increases in domestic violent crimes were noted (Zahran et al. 2009). Not only does this study consider all 67 counties in Florida but with the period of study (1991-2005) chosen, the authors were able to take account of the 34 major disasters that occurred. These major disasters included hurricanes, floods, wildfires, and drought. Leitner and Helbich (2011), on the other hand, studied the state of Louisiana, though the focus was on a single natural disaster – hurricane Katrina. The results pointed to stable crime rates in some regions, whilst a decline was characteristic of other areas in Louisiana.

The crime literature, which is quite extensive, also features research that considers the impact of unemployment and income on crime. Majority of research establishing the nexus between crime and unemployment have not examined a comprehensive list of criminal activities. Nevertheless, they add to the body of literature and assist in laying the foundation for future research. For instance, studies have established a positive impact of unemployment on property crimes (Chiricos 1987; Raphael and Winter-Ebmer 2001; Lin 2008; Fougére et al. 2009). Raphael and Winter-Ebmer, for instance, instrumented unemployment rates with oil shocks, and found positively significant effects of unemployment on property crimes, but weak support for rape. Other authors, such as Cantor and Land (1985), were unable to establish a stable relationship of unemployment with rape. Cantor and Land (1985) and Melick (2003) reported a negative impact of unemployment on motor vehicle theft. Cantor and Land found negative partial effects on motor vehicle theft, while Melick estimated that 22 fewer cars per 100,000 of the population will be stolen for every one percentage point increase in unemployment. For homicides, studies have maintained either a negative effect (Cantor and Land 1985) or no effect (Yang and Lester 1994). Some crime studies utilized income as a control variable, hypothesizing that it does influence the occurrence of criminal activities. Hollis (2011) for example, estimated that an increase in income per capita results in 0.0017 decline in property crimes during the 2007 to 2008 economic recession. This negative relationship is also supported by Raphael and Winter-Ebmer (2001) who showed that income per worker negatively affects property crimes; this impact was also demonstrated for violent crime rates. Other studies have highlighted the impact of income on crime by using various measures of income including those that capture the economic conditions of individuals (Grogger 1998; Gould et al. 2002; Machin and Meghir 2004; Lin 2008). The foregoing studies underscore the fact that there are other determinants of crime, namely, unemployment and income. Thus, in order to correctly estimate the effect of hurricanes, this study includes unemployment and income as control variables in the estimation process.

II. Modeling Hurricanes Shocks

The difference-in-difference (DID) technique is widely used by some to determine the impact of hurricanes on key economic variables, including crime. This technique compares the changes in the dependent variable from the pre-shock and post-shock periods for an affected (treatment) group to changes for the same periods for an unaffected (control) group. The affected group experiences the hurricane shock, while the latter group remains unaffected. With DID, there is an assumption that on average, both groups experience the same changes; that is, there is a common trend in the absence of the treatment. As it relates to crime, Hussey et al. (2011) used this approach to analyze the effect that hurricane Katrina migrants had on crime rates in New Orleans and Houston. Treating Katrina as exogenous to the model, the authors estimated a two-way fixed effects panel regression. The fixed effects controlled for unobservable characteristics across time and cities. This approach have been used in other research areas; for example, a wide range of studies estimated the impact of hurricanes on labour market outcomes using the difference-in-difference approach (including McIntosh 2008; Groen and Polivka 2008).

In contrast to Hussey et al. (2011), this study applies a more general approach – namely, generalized difference-in-difference. The generalized difference-in-difference (GDD) approach is an improvement upon the difference-in-difference technique. This improvement came about due to criticisms of the difference-in-difference approach having one experimental group (affected group), and the failing to identify an appropriate control group (that is, the unaffected or comparison group) (Angrist and Krueger 1999; Belasen and Polachek 2008). To get around the weaknesses with difference-in-difference, the latter authors studied the impact of hurricanes on the labour market in Florida by using many experimental groups, and many control groups. This generalized approach compares a county that is directly hit by a hurricane to those that are not hit; it also takes account of the fact that when a county is hit, neighboring counties can also be affected. In the disaster study done by Zahran et al., a binomial count model was used to take account of the count nature of the crimes committed. In this present study, however, the objective is to take account of the fact that when a hurricane strikes, not all counties are hit; that is, there are some that remain unaffected. A count model cannot take account of this characteristic, thus, the GDD is deemed more appropriate for the hurricane data. A more formal description is presented in the model specification section.

Though Hussey et al. (2011) relied on the DID approach to study the impact of hurricanes on crime, thus far, there has been no application of the GDD model to crime data. In the Belasen and Polachek (2008) study, they incorporated all 67 counties in Florida. These counties formed the experimental and control groups, where a comparison of the counties that were hit by hurricanes was made to the counties that were not hit. When a hurricane strikes, it can affect more than one county at the same time, and impact neighboring counties. In light of this, Belasen and Polachek not only took account of counties hit and those not hit, but also those counties that were neighboring those experiencing the direct impact. From the foregoing, one can easily fit this study within the framework that Belasen and Polachek used.

As mentioned above, the GDD approach is able to isolate neighboring impacts. With regards to crime, neighboring effects are quite important. Quarantelli and Dynes (1970) pointed out that with civil unrests, looting is carried out by locals but with regards to natural disasters, looting is carried out by people living outside of the affected areas. Thus, one has to consider the possibility of hurricane shocks creating unintended changes in criminal activities in counties that are not directly stricken.

III. Data

The dataset for this paper is based on a panel of the 67 counties in Florida from 1976 to 2012. Hurricane data comes from the National Oceanic and Atmospheric Administration (NOAA). This administration provides historical hurricane tracks that trace out the path of past hurricanes.[1] See Table 1 for hurricanes experienced during this period. The strength or category (based on wind speeds) of the hurricanes are also provided. These tracks show the counties that are directly hit, those that are unaffected as well as those neighboring the counties that received direct impacts from the storms. The data picked up from these tracks show the changes in hurricane strength as the storms made their way through Florida. Thus, one is able to take account of these changes in constructing the hurricane variables. Crime data are from two main sources: Florida Department of Law Enforcement (FDLE) and the United States Federal Bureau of Investigation (FBI) Uniform Crime Reporting. Data on seven types of criminal activities are: aggravated

[1] To see hurricane tracks, go to http://csc.noaa.gov/hurricanes/#.

assault, burglary, forcible rape, larceny, motor vehicle theft, murder, and robbery. See Tables 2 and 3. The FDLE ended its monthly reports on crime data in 1996 and began producing reports on a semi-annual basis since 1997. Thus, there are two reports published per year. The first reports crime taking place from January to June, and the second is an annual report. From the annual report, one can calculate the number of crimes for the period July to December. Due to this change in reporting, the data set is restricted to having two data points per year per county. The FBI stores data received from the FDLE so the monthly crime data are accessible for 1976 to 1996 from the former agency. This monthly data are aggregated to obtain semi-annual figures from 1976 to 1996.

This study also uses unemployment and population data. The unemployment data is from the Local Area Unemployment Statistics (LAUS), and are defined as the number of persons who have made efforts to find employment as well as those who have been laid off, and are waiting to be recalled. Though the hurricane, crime and population data are available for earlier dates – the availability of the unemployment data restricts the time period for this study. Regarding unemployment – from 1976 to 1989 – LAUS makes it clear that the data at the sub-state (county) level are not consistent with the data 1990 and beyond. The methodologies are inconsistent. This inconsistency is taken into account in the regression modelling. The population data are provided by the Florida Legislative Office of Economic & Demographic Research.

IV. Model Specification

This section provides the details of the generalized difference-in-difference (GDD) technique. This technique is general in the sense that there are many affected counties, many unaffected counties (acting as controls or comparison groups) that are being studied over many hurricanes. The difference-in-difference is captured as the difference in crime per capita as a function of the hurricane difference – that is, whether a hurricane strikes or not. GDD examines the change in crime per capita by county when there is a hurricane compared to a change in crime per capita when there is no hurricane relative to other areas. The model takes the following form for each of the seven (7) crime categories:

$$\left(\frac{Crime_{it}}{Pop_{it}} - \frac{Crime_{it-1}}{Pop_{it-1}}\right) = \beta_1 + \beta_2 H_{it}^{D12} + \beta_3 H_{ijt}^{N12} + \beta_4 H_{it}^{D35} + \beta_5 H_{ijt}^{N35} + \beta_6 (Unemp_{it} - Unemp_{it-1}) + \beta_7 D$$
$$+ \beta_8 (Unemp_{it} - Unemp_{it-1}) * D + \beta_9 Y_{it} + c_i + y_t + s_f + t_c + u_{it-1}$$

$Crime_{it} / Pop_{it}$ is crime per capita for county i in period t. This is calculated as the number of reported crimes divided by the population. The dependent variable is therefore the difference in crime per capita between period t and $t-1$ (a period earlier) for county i. This allows for a direct comparison to be made between crime per capita this period and the period before.

The typical size of a hurricane is approximately 300 miles wide from the eye of the hurricane; thus, the hurricane force winds can extend over a great distance (NOAA 1999). Given the historical paths of hurricanes, especially the ones in this study, the storms do not always pass through the center of a county. At times, the hurricane paths are usually more to the left or more to the right of the counties in the path of the hurricanes. As a result, the immediate neighbors of the counties in the path of the hurricane receive an impact just as great as those directly struck given the typical size of a hurricane. According to NOAA (1999), the outer rain bands consist of dense lines of thunderstorms, which can extend up to tens of miles wide and up to 300 miles long. Thus, the counties bordering those receiving the intensity of a hurricane likely experience heavy rains and thunderstorms; but not the sort of destruction that the directly hit counties experience.

In light of the foregoing, the counties that receive the *direct impact* are those in the direct path of the hurricane as well as the first (immediate) neighboring counties. The ones that experience the *neighboring effects* from the storms are the second neighbors – these can be considered as the *real* neighbors if we group the ones through which the hurricanes travelled as the first neighbors. With that said, all hurricane variables are dummy variables. H_{it}^{D12} captures the *direct impact* from a weaker hurricane, whereas, H_{ijt}^{N12} captures the *neighboring effects* on counties bordering those that received direct impact. Thus, counties i and j are located next to each other and so if a hurricane strikes county i and j borders i, then j can experience the effects though indirectly. H_{it}^{D12} takes a value of one if a hurricane directly affected county i and zero otherwise, while H_{ijt}^{N12} is assigned a value of one if county j was affected when county i got stricken and zero otherwise.

Weak hurricanes are those falling into categories 1 and 2 on the Saffir-Simpson Scale. They travel at wind speeds ranging from 76 to 95 miles per hour, and 96 to 100 miles per hour respectively. These winds are dangerous, and require being proactive to protect lives and property before the attack of such storms. H_{it}^{D35} and H_{ijt}^{N35} carry the same interpretation but for stronger hurricanes. Strong or major hurricanes are those falling into categories 3 to 5 where wind speeds range from 111 to 129 miles per hour, 130 to 156 miles per hour and at least 157 miles per hour respectively. Storms with these characteristics are considered to be catastrophic and require paying more than the usual attention to precautionary measures. While it is true that hurricane strikes are expected, a strike is exogenous in the sense that, its path, the timing of its occurrence cannot be completely determined (Belasen and Polachek 2008; Spencer and Polachek 2015). The hurricane variables are therefore assumed to be exogenous. In addition, since the hurricane variables are the variables of interest, one can assume that their coefficients are unbiased. Particularly, in controlling for fixed effects, which capture the possible endogenous distributional effects of hurricanes striking locally, one is just left with the actual hurricane shocks which are exogenous.

Unemployment is captured as $Unemp_{it} - Unemp_{it-1}$. This allows for a comparison between unemployed individuals between t and t-1 (a period earlier) for county i. Moreover, Cantor and Land (1985) pointed out the importance of lagged effects of unemployment on crime, which are quite short in duration, and captured its effect by incorporating the difference between unemployment in time t and time t-1. D captures the change in definition of the unemployment variable, where $D = 0$ if t goes from 1976 to 1989, and $D = 1$ if t goes from 1990 to 2012. y_t and c_i are time period and county fixed effects respectively. Time period fixed effects control for variations for all time periods. The specification of the model also removes the time-invariant county specific factors that affects crime. The importance of controlling for seasonal fluctuations has been established by the seasonality and crime trend literature which points out that the timing of criminal activities might be related certain times of the year. For example, assaults during public holidays (Harries et al. 1984); robbery in winter, and homicides in summer (Landau & Fridman 1993); domestic burglary during first four months of the year, and domestic disputes during July and August (Farrell and Pease 1994); property crimes in months with pleasant weather (Hipp et al. 2004); and assaults in summer (Breetzke & Cohn 2012). Taking into account the position of the literature regarding seasonality, s_f, semi-annual fixed effects is included in the model to hold fix any seasonal peculiarities that might exist. Finally, t_c, the county-specific time trend is included to control for structural variations within counties that are caused by factors that are county specific overtime. Including all these fixed effects excludes all variability in the data.

Biases can result from the under-reporting of crime, and the quality of the police force (Coronado and Orrenius 2005). The FDLE is not specific on the types of under-reporting, but in speaking on crimes reported in the United States, Warner (1931) mentioned that a policeman may record a type of offense as being in another category. He also used the example of a motor vehicle where the owner may park his car in one area, forget where the car is parked, and report the car as being stolen. In the latter example, there is over-reporting. As it relates to the quality of the police force, the FDLE has no documentation; however, as Hussey et al. (2011) stated, more policemen increases the number of offences that get reported. Thus, these controls help the identification strategy to be dependent upon the residual variation between crimes and hurricanes. The interaction between the change in unemployment and in the definition of unemployment is captured by $(Unemp_{it} - Unemp_{it-1}) * D$. The presence of a significant interaction term indicates that the change in the definition of unemployment has an effect on crime per capita. Finally, Y_{it} represents income per capita. As indicated before, this is important to the analysis since earnings can impact the level of crime.

V. Diagnostic Tests

Serial correlation in panel models can result in biased standard errors, and less efficient estimates. The Woolridge (2002) panel data test assessed whether the residuals from a regression of first differenced variables on their lags are serially correlated. This test also takes into consideration correlation within panels by correcting for clustering at the panel level. This adjustment results in the test being robust to conditional heteroskedasticity (Drukker 2003). Studies using crime data from FBI Crime reporting as well as other research have generally tested for serial correlation. For example, Coronado and Orrenius (2005) utilized feasible generalized least squares to account for county-level heteroscedasticity, and correlation within counties and across time. In this current study, the test is implemented using a simple user-written STATA command done by Drukker (2003). The test indicates the presence of autocorrelation; thus, the model is fitted using feasible generalized least squares (FGLS).

VI. Discussion of Results

This section will first discuss the outcomes from weak hurricanes followed by results emanating from strong hurricanes. As can be seen from Table 4a below, a direct strike increases crime per capita for all seven crime categories. Larceny per capita increases by 0.0155 representing an unlawful increase in the taking away of one's property by 1550 per 100,000 inhabitants. This increase is greater than the positive changes in aggravated assault, burglary, forcible rape, motor vehicle theft, murder and robbery. Following larceny, are burglaries which increase by 0.0056 or 560 unlawful entries to commit theft per 100,000 inhabitants. Frailing and Harper (2007), and Leitner and Helbich (2010) also reported significant increases in burglary due to the passages of hurricanes. The latter authors alluded to the fact that the mandatory evacuation order issued in Houston was not strictly observed, and so those remaining behind engaged in unlawful entry into the houses of the evacuees to commit theft. Aggravated assault per capita and motor vehicle theft per capita also increase by 0.0021 and 0.0026 or 210 and 260 per 100,000 respectively. Smaller increases are also seen for robbery, forcible rape and murder. All these increases have been found in the literature (including LeBeau 2002; Thornton and Voigt 2007; Leitner and Helbich 2010; Varano et al. 2010; Hussey et al. 2011). For example, Thornton and Voight (2007) reported that women became rape victims in the wake of hurricane Katrina. Their work alluded to the fact that women become vulnerable during different stages of a disaster event, which could be as a result of no form of protection from national security. Hussey et al. (2011) estimated an increase in number murder associated with an evacuation shock. They also found significant increases in aggravated assault. Their results pointed to possible inadequate federal protection to curb criminal activities. In general, increases in crime seem to result from the expectation that people will leave their homes and properties if hurricane threaten to affect specific areas. However, significant increases in unlawful activities appear to result from insufficient security resources or a lack thereof.

In contrast to the positive impacts on counties directly struck, one can observe declines in the neighboring counties for all crime categories except murder, which increases by a significantly small amount, that is, 0.4 per 100,000 inhabitants. For neighboring counties, we also see the highest decline of 230 per 100,000 inhabitants in larceny relative to the other crime categories. As Table 4a shows, Florida experienced increases in crime per capita across all criminal activities in counties directly hit by stronger hurricanes. Once again, we observe more larceny acts than all other criminal activities; that is, for every 100,000 inhabitants we see an increase of 150 larcenies. Next in line is burglary, which saw an increase of 500 per 100,000 individuals. All increases are in the same order as with the weaker storms. As was noted earlier, the literature features studies that find positive impacts. However, negative impacts are also featured (Bailey 2009; Zahran 2009; Varano et al. 2010). In this study, we see such negative impacts only in the neighboring counties. As with the weaker storms, the neighbors experienced a larger decline in larceny per capita (310 per 100,000) relative to the other crimes. Comparing the results across hurricane strengths, it should be noted that stronger hurricanes have less impact than the weaker ones. An argument to support this observation is that with stronger storms, there is more destruction of property and related damages, as well as the possibility of more deaths and injuries. Said differently, there less to steal, fewer people to victimize, and offenders themselves may be preoccupied with getting resettled. In addition, criminals may be concerned about their safety so they are less involved in unlawful activities.

Finally, Table 4b displays the remaining results of the model. As can be seen from the table, with the exception of aggravated assault, which is insignificant, unemployment has the expected sign of having a positive and significant effect on crime per capita. D, which captures the change in definition of the unemployment variable has a significant and negative sign across all categories. This change in definition is deemed to be more accurate in capturing unemployment. The interaction between unemployment and D is mostly negative and significant. Therefore, holding all else constant, from 1990 to 2012, crime per capita has been lower in comparison to the 1976 - 1989 period. Finally, the results on income per capita shows that as earnings increase, crime decreases by an estimated amount of 10 to 140 incidences depending on the type of offence.

VII. Robustness Checks

To corroborate the story that neighboring counties experience reduction in crime per capita, while the opposite happens for directly hit counties, the hurricane variable capturing the direct impact is readjusted. In this instance, the immediate (first) neighbors to the counties through which the hurricanes passed are excluded; leaving the counties through which the hurricanes tracked as the only ones receiving direct impact. The second neighbors remain as the neighboring counties. In general, the results remained the same except for aggravated assault wherein a strong hurricane resulted in a negligible increase for a neighboring hit; and a negative effect for robbery and forcible rape for a direct hit. The latter effects are very minute – an almost zero impact. This adjustment demonstrates that the initial assignment of counties that received direct impacts and the neighbors are not arbitrary. To add, high crime counties such as Miami-Dade are dropped from the panel to see if the story would change. However, exclusion of such counties does not change the conclusion.

IX. Conclusion

The extent to which natural disasters affect crime is widely studied in the literature. Empirical studies reveal that natural disasters can have a positive, negative or no impact on criminal activities. Hurricanes are one type of natural disaster that receive a lot of attention. From the growing literature, hurricanes seem to have mostly a positive impact on crime although negative effects are also noted. However, this study hypothesized that hurricanes will have a positive impact on crime, and that stronger storms will have a greater impact than weaker storms. Thus, the study investigated whether the impacts that hurricanes have on criminal activities are also observed in Florida from 1976 to 2012. By using a generalized difference-in-difference approach, this study uses a more insightful analysis than previous studies. The approach allows one to take account of hurricane strikes in directly hit counties as well as those neighboring. Furthermore, the approach allows an isolation of the impact that weak and strong hurricanes has on crime per capita. The approach estimates an increase in criminal activities in directly hit counties both for weak and strong hurricanes. Overall, neighboring counties experience a decline in criminal activities. The results also point to criminals using hurricanes as an employment creating mechanism, where they become predators of vulnerable individuals.

The quantification of hurricane strikes from this study has several implications. The estimated impacts help affected individuals as well as the law enforcement teams in Florida to understand the likely impacts on crime per capita in directly hit counties as well as neighboring counties both for strong and weak hurricanes. Governments have often been criticized for their slow response rates in assisting disaster victims; the shortage of police forces, and the public policies on emergency management (Munasinghe 2007). Therefore, knowledge of the possible changes in crime per capita can inform national security policy regarding the allocation resources in the face of natural disasters. The proper allocation of resources can not only prevent unnecessary delays in maintaining social order, but also in curbing the economic cost of crime. Additionally, individuals and families can take precautionary measures for their own safety.

The implications of this study arise from results demonstrating that hurricanes can impact crime in different ways, and the magnitude of the impact depending on the whether a county is in the immediate path of the hurricane. However, it must be noted that UCR crime data depends on police documenting reports of unlawful activities. These reports might be limited by the slow response of law enforcement or the incapacity of victims to report crime. If the latter takes place, then this might misrepresent the true nature of criminal activities. Future research can consider incorporating other measures of crime such as those capturing available federal resources.

References

Ali, Z. 2013. "Media Myths and Realities in Natural Disasters." *European Journal of Business Social Sciences* 2 (1), 125-133.

Anderson, C. and Anderson, K. 1998. Temperature and Aggression: Paradox, Controversy, and a (Fairly) Clear Picture. Chapter in R. Geen & E. Donnerstein (Eds.) Human aggression: Theories, Research and Implications for Policy. (pp. 247-298). San Diego, CA: Academic Press.

Angrist, J. A. and Krueger, A.B. 1999. "Empirical Strategies in Labor Economics." In Orley C. Ashenfelter and David A. Card, editors, *Handbook of Labor Economics*, 3A, Amsterdam: Elsevier, 1277-1366.

Bailey, K. 2009. "An Evaluation of the Impact of Hurricane Katrina on Crime in New Orleans, Louisiana." *Applied Research Projects*, Texas State University-San Marcos.

Baron, R. 1978. Aggression and Heat: The Long Hot Summer Revisited. In A. Baum, J. E. Singer & S. Valins, (Eds), the Urban Environment. Hillsdale, NJ: Erlbaum, pp. 57-84.

Bass, L. 2008. "A Pooled Time Series Analysis of Hurricane Katrina Evacuees and their Effect on Crime Rates." Paper presented at the *66th Midwest Political Science Association Annual National Conference*, Chicago, IL, April 3-7.

Becker, G. 1968. "Crime and Punishment: An Economic Approach." *Journal of Political Economy*, 76(3):169-217.

Belasen, A., and Solomon W. Polachek. 2008. "How Hurricanes Affect Wages and Employment in Local Labor Markets." *American Economic Review: Papers and Proceedings* 98 (2), 49-53.

Bell, P. 1992. "In Defense of the Negative Affect Escape Model of Heat and Aggression." *Psychological Bulletin*, 111, 342-346.

Berkowitz, L.1993. Aggression: Its Causes, Consequences, and Control. New York, McGraw-Hill, 485.

Blake, E., Landsea, C. and Gibney, E. 2011. "The Deadliest, Costliest and Most Intense United States Tropical Cyclones 1851-2010." *NOAA Technical Memorandum NWS NHC-6*.

Breetzke, G. and Cohn, E. 2012. "Seasonal Assault and Neighborhood Deprivation in South Africa Some Preliminary Findings." *Environment and Behavior* 44 (5), 641-667.

Cantor, D. and Land, K. 1985. "Unemployment and Crime Rates in the Post-World War II United States - A Theoretical and Empirical Analysis." *American Sociological Review* 50:3, 317-332.

Chiricos, Theodore. 1987. "Rates of Crime and Unemployment: An Analysis of Aggregate Research Evidence." *Social Problems* 34 (2), 187-212.

Clarke, R. and Cornish, D. 1985. "Modeling Offenders' Decisions: A Framework for Research and Policy." in M. Tonry and N. Morris, eds., *Crime and Justice,* IV. 147-85. Chicago: University of Chicago Press.

Cohen, L. and Felson, M. 1979. “Social Rate and Crime Rate Trends: A Routine Activities Approach.” *American Sociological Review* 44:588-608.

Coronado, R. and Orrenius, P. 2005. “The Impact of Illegal Immigration and Border Enforcement on Crime Rates Along the U.S. – Mexico Border,” *Working Paper 131* Federal Reserve Bank of Dallas.

Cromwell, P., Dunham, R., Akers, R and Lanza-Kaduce, L. 1995. “Routine Activities and Social Control in the Aftermath of a Natural Catastrophe.” *European Journal of Criminal Policy and Research* 3: 56-69.

Curtis, T., Miller, B, and Berry, H. 2000. “Changes in Reports and Incidence of Child Abuse Following Natural Disasters.” *Child Abuse and Neglect,* 24:9, 1151–1162.

Davila, M., Marquart, J and Mullings, J. 2005. “Beyond Mother Nature: Contractor Fraud in the Wake of Natural Disasters Deviant Behavior.” *Deviant Behavior*, 26:3.

Drukker, D. 2003. “Testing for Serial Correlation in Linear Panel-Data Models.” *The Stata Journal* 3:2, 168-177.

Farrell, G. and Pease, K. 1994. “Domestic Disputes and Residential Burglary in Merseyside 1988—90.” *The British Journal of Criminology*, 34(4), 487-498.

Federal Bureau of Investigation (FBI). 2004. “Uniform Crime Reporting Handbook.” http://www2.fbi.gov/ucr/handbook/ucrhandbook04.pdf. Accessed June 4, 2013.

Fougére, D., Kramarz, F and Pouget, J. 2009. “Youth Unemployment and Crime in France.” *Journal of European Economic Association* 7:5, 909-938.

Frailing, K. and Harper, D.W. 2007. “Crime and Hurricanes in New Orleans.” In the *Sociology of Katrina: Perspectives on a Modern Catastrophe*, ed. D.L. Brunsma, D. Overfelt, and J.S. Picou, p 51-68.

Gould, E., Weinberg, B. and Mustard, D. 2002. “Crime Rate and Local Labor Market Opportunities in the U.S.: 1979-1997.” Review of Economics and Statistics 84:1, 45-61.

Groen, J.A., and Polivka, A. E. 2008. “The Effect of Hurricane Katrina on the Labor Market Outcomes of Evacuees.” *American Economic Review* 98 (2), 43–48.

Grogger, J. 1998. “Market Wage and Youth Crime.” Journal of Labor Economics 16:4, 756-91.

Harries, K., Stadler, S. and Zdorkowski, T. 1984. “Explorations in Inter-Neighborhood Variation, Dallas 1980.” Annals of the Association of American Geographers, 74:4, 590- 604.

Hipp, J., Bauer, D., Curran, P and Bollen, K. 2004. “Crimes of Opportunity or Crimes of Emotion? Testing Two Explanations of Seasonal Change in Crime.” *Social Forces* 82 (4), 333-1372.

Hollis, C. 2011. "Identifying the effect of unemployment on property crimes: Analyzing the impact of the 2007/2008 economic recession." Thesis, Graduate School of Arts and Sciences of Georgetown University.

Horrocks, J. and Menclova, A. 2011. The Effects of Weather on Crime. *New Zealand Economic Papers* 45:3.

Hussey, A., Nikolsko-Rzhevskyy, A and Pacurar, I.S. 2011. "Crime Spillovers and Hurricane Katrina." Department of Economics, University of Memphis.

Landau, Simha and Daniel Fridman. 1993. "The Seasonality of Violent Crime: The Case of Robbery and Homicide in Israel." *Journal of Research in Crime and Delinquency*, 30 (2), 163-191.

LeBeau, J. 2002. "The Impact of a Hurricane on Routine Activities and on Calls for Police Service: Charlotte, North Carolina and Hurricane Hugo." *Crime Prevention and Community Safety: An International Journal* 4: 53-64.

Leitner, M. and Helbich, M. 2011. "The Impact of Hurricanes on Crime in the City of Houson, TX: A Spatial-Temporal Analysis." Presented at the ASPRS/CaGIS 2010 Fall Specialty Conference November 15-19, 2010 Orlando Florida.

Lin, Ming-Jen. 2008. "Does Unemployment Increase Crime? Evidence from U.S. Data 1974 2000." *The Journal of Human Resources* 43 (2), 413-436.

Machin, S., and Meghir, C. 2004. "Crime and Economic Incentives." Journal of Human Resources 39 (4):958-79.

McIntosh, M. F. 2008. "Measuring the Labor Market Impacts of Hurricane Katrina Migration: Evidence from Houston, Texas." *American Economic Review: Papers and Proceedings* 98:2, 54-57.

Melick, M. 2003. "The Relationship between Crime and Unemployment." *The Park Place Economist* 11(1), 30-36.

Moos, R. 1976. The Human Context: Environmental Determinants of Behavior. New York: John Wiley and Sons.

Munasinghe, M. 2007. "The Importance of Social Capital: Comparing the Impacts of the 2004 Asian Tsunami on Sri Lanka, and Hurricane Katrina 2005 on New Orleans." *Ecological Economics* 64(1), 9-11.

National Oceanic Atmospheric Administration. 1999. "Hurricane Basics." U.S. Department of Commerce.

Quarantelli, E. and Dynes, R. 1970. "Property Norms and Looting: Their Patterns in Community Crisis." *Phylon* 31: 2, 168-182.

Raphael, S. and Winter-Ebmer, R. 2001. “Identifying the Effect of Unemployment on Crime.” *The Journal of Law & Economics* 44:1, 259-283.

Spencer, N. and Polachek, S. 2015. “Hurricane Watch: Battening Down the Effects of the Storm on Local Crop Production.” *Ecological Economics* 120 234-240.

Taylor, A. 1989. “Victims of Crime as Victims of Disaster Australian and New Zealand.” *Journal of Psychiatry*, 23:3.

Thornton, W. and Voigt, L. 2007. “Disaster Rape: Vulnerability of Women to Sexual Assaults during Hurricane Katrina.” Journal *of Public Management and Social Policy* 13:2, 23-49.

Varano, S., Schafer, J., Cancino, J., Decker, S and Greene, J. 2010. “A Tale of Three Cities: Crime and Displacement after Hurricane Katrina.” *Journal of Criminal Justice*, 38, 42-50.

Walker, W., Sunhui S. and Keys-Mathews, L. 2012. “The Impact of Hurricane on Spatial-Temporal Patterns of Crime in Mobile, Alabama.” University of North Carolina.

Warner, S. 1931. “Crimes Known to the Police: An Index of Crime?” *Harvard Law Review* 45:2, 307-334.

Wenger, D. and Friedman, B. 1986. “Local and National Media Coverage of Disaster: A Content Analysis of the Print Media’s Treatment of Disaster Myths.” *International Journal of Mass Emergencies and Disasters* 4(3), 27-50.

Woolridge, J. 2002. Econometric Analysis of Cross Section and Panel Data. Cambridge MA: MIT Press.

Yang, B. and Lester, D. 1994. "Crime and Unemployment." *The Journal of Socio Economics* 23:1-2, 215-222.

Zahran, S., O'Connor Shelley, T and Peek, L. 2009. "Natural Disasters and Social Order: Modeling Crime Outcomes in Florida." *International Journal of Mass Emergencies and Disasters* 27(1), 26-52.

Appendix

Table 1: Hurricane Descriptive Statistics

Hurricane	Synoptic Lifecycle	Year	Saffir Simpson Scale
David	August	1979	2
Frederick	August	1979	4
Bob	July	1985	1
Elena	August	1985	3
Kate	November	1985	2
Florence	September	1988	1
Floyd	October	1987	1
Andrew	August	1992	4
Allison	June	1995	1
Erin	August	1995	1
Earl	September	1995	1
Opal	September	1995	3
Danny	July	1997	1
Georges	September	1998	2
Irene	October	1999	1
Gordon	September	2000	1
Charley	August	2004	4
Frances	September	2004	2
Jeanne	September	2004	3
Ivan	September	2004	3
Dennis	July	2005	3
Katrina	August	2005	1
Rita	September	2005	1
Wilma	October	2005	3

Table 2: Crime Descriptive Statistics

Crime Categories	Mean	Std. Dev.	Min	Max
Murder	30.9	47.7	0	371
Forcible Rape	69.9	104.7	0	1320
Robbery	226.2	601.9	0	9870
Aggravated Assault	457.2	1034.4	0	14421
Burglary	1208.0	2369.1	0	28098
Larceny	2936.1	6605.2	0	85359
Motor Vehicle Theft	467.5	1390.4	0	24084

Table 3: Uniform Crime Reporting: Definition of Violent Crimes (Source: FBI, 2004)

Aggravated Assault	An unlawful attack by one person upon another for the purpose of inflicting severe of aggravated bodily injury
Burglary	The unlawful entry of a structure to commit a felony or a theft
Forcible Rape	The carnal knowledge of a female forcibly and against her will
Larceny	The unlawful taking, carrying, leading or riding away of property from the possession or constructive possession of another
Motor Vehicle Theft	The theft or attempted theft of a motor vehicle
Murder	The willful killing of one human being by another
Robbery	The taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear

Table 4a: Hurricane Effects for Major Criminal Activities

	Larceny	Burglary	Aggravated Assault	Robbery	Forcible Rape	Motor Vehicle Theft	Murder
Saffir Simpson Scale 1-2							
Direct Effect	.0155***	.0056***	.0021***	.0008***	.0002***	.0026***	.00001***
	(.00010)	(.00007)	(.00003)	(9E-06)	(3E-06)	(.00003)	(7E-07)
Neighboring Effect	-.0023***	-.0004***	-.0005***	-.0002***	-.0001***	-.0004***	4E-06***
	(.00004)	(.00004)	(.00002)	(6E-06)	(2E-06)	(.00001)	(8E-07)
Saffir Simpson Scale 3-5							
Direct Effect	.0015***	.0005***	.0003***	.00002***	.00001***	.00034***	3E-06**
	(.00008)	(.00006)	(.00002)	(4E-06)	(3E-06)	(.00002)	(1E-06)
Neighboring Effect	-.0031***	-.0008***	-.0002***	-.0002***	-.00005***	-.00044***	-8E-06***
	(.00008)	(.00006)	(.00003)	(10E-06)	(4E-06)	(.00002)	(1E-06)
Observations	4824	4824	4824	4824	4824	4824	4824

*****, **, * Significant at the 1%, 5% and 10% levels; () – standard errors**

Table 4b: Control Variables for Major Criminal Activities

	Larceny	Burglary	Aggravated Assault	Robbery	Forcible Rape	Motor Vehicle Theft	Murder
Unemployment	9E-09***	5E-09 ***	-2E-10	3E-09***	1E-10***	3E-09***	8E-11***
	(9E-10)	(6E-10)	(3E-10)	(1E-10)	(2E-11)	(4E-10)	(8E-12)
D	-.0064***	-.0048***	-.0030***	-.0008***	-.0003***	-.0017***	-.0001***
	(.00002)	(.00002)	(3E-06)	(1E-06)	(6E-07)	(5E-06)	(3E-07)
Unemployment*D	4E-09	-2E-09**	2E-09***	-3E-09***	-1E-10***	-9E-12	-1E-10***
	(1E-09)	(7E-10)	(3E-10)	(2E-10)	(3E-11)	(4E-10)	(8E-12)
Income per capita	-.0014***	-.0004***	-.00005***	-.0008 ***	-.0001***	-.0002***	-.0001***
	(.00004)	(.00003)	(.00001)	(5E-06)	(4E-06)	(9E-06)	(2E-06)
Observations	4824	4824	4824	4824	4824	4824	4824

******, **, * Significant at the 1%, 5% and 10% levels; () – standard errors***