Spatial patterns of off-the-system traffic crashes in Miami–Dade County, Florida, during 2005–2010

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Abstract

Objective: The objective of this study is to analyze the spatial distribution of the vehicles involved in crashes in Miami–Dade County. In addition, we analyzed the role of time of day, day of the week, seasonality, drivers’ age in the distribution of traffic crashes.

Method: Off-the-system crash data acquired from the Florida Department of Transportation during 2005–2010 were divided into subcategories according to the risk factors age, time of day, day of the week, and travel season. Various spatial statistics methods, including nearest neighbor analysis, Getis-Ord hot spot analysis, and kernel density analysis revealed substantial spatial variations, depending on the subcategory in question.

Results: Downtown Miami and South Beach showed up consistently as hotspots of traffic crashes in all subcategories except fatal crashes. However, fatal crashes were concentrated in residential areas in inland areas.

Conclusion: This understanding of patterns can help the county target high-risk areas and help to reduce crash fatalities to create a safer environment for motorists and pedestrians.

Introduction

Over 30,000 people are killed in the United States each year because of car crashes. Car crashes cost the country about $41 billion in medical and job loss costs annually (CDC 2016). In Florida, car crashes cost the state about $3.16 billion annually (CDC 2005). According to the NHTSA (2012), from 2008 to 2012, there was an average of 2,500 traffic fatalities per year and 3,500 drivers involved in fatal crashes per year in Florida. According to the Florida Department of Transportation, Florida was above the U.S. average in fatalities per 100,000 population and fatalities per 100 million vehicle miles traveled in 2010. In Miami–Dade County, there were about 250 traffic fatalities per year. Miami–Dade County ranks first in total fatalities and fatal crashes per year in the state of Florida (NHTSA 2012).

There are many risk factors that influence car crashes and some of their resulting injuries. The following sections consist of a brief review of literature examining factors influencing traffic crashes.

Sociodemographic factors

Driver age and gender are 2 of the most common risk factors among studies that have assessed the risk factors involved in traffic crashes (Abdel-Aty and Radwan 2000; Hijar et al. 2000; Yau 2004). The study conducted by Hijar et al. (2000) used characteristics of the driver as a variable. Driver characteristics included age, gender, years of experience as a driver, continuous driving time until the crash, use of a seat belt, and alcohol consumption. Their analyses indicated that the most significant risk factor was for drivers who were under the age of 25 and over the age of 45. Another study by Valent et al. (2002) of fatal road crashes in Udine, Italy, concluded that the risk increased with age. Older people were more likely to be involved in a crash. Abdel-Aty (2003) found the driver’s age to be a significant factor in the severity of injury involved in a traffic crash.

Alcohol is a major factor in crash occurrence and also for fatality in a car crash. Sangal et al. (2015) studied the effects of alcohol on driver behavior that cause traffic crashes. Additionally, Abdel-Aty (2003) analyzed variables related to the vehicle, driver, roadway, and environmental conditions for the injury severity of people involved in traffic crashes in 1996 and 1997 in Central Florida. His analyses for the roadway sections that involved alcohol found that driving under the influence was not significant, but the interaction between the influence of alcohol and using a seat belt were. In this context, there is limited research that has addressed the question of the proximity of bars as an effect on the number of crashes.

Household income and poverty level also have an effect on the number of crashes. Huang et al. (2010) discussed the relationship between crash risk and socioeconomic factors at the county level within Florida. Their results revealed that higher median household income and lower unemployment rate do not show a statistical significance to the number of
crashes that occur in the area. However, areas with a higher rate of deprivation tend to have higher risk for severe crashes. Therefore, driver characteristics such as age, gender, alcohol consumption, and deprivation are significant factors in traffic crashes.

External factors

Many studies have also used day of the week as a risk factor for crashes and determining severity of injuries in traffic crashes. An earlier study by Pigman et al. (1990) analyzed data reported to the Kentucky State Police on the rural highway system in terms of differences and characteristics specifically on weekdays, weekends, and holidays. The results of the study indicated that the largest number of crashes occurred on weekends, with Saturday, Friday, and Sunday being the 3 days with the highest number of crashes, in that order. On rural roads, the percentage of crashes occurring on weekends showed a declining trend. Throughout the study, there were more crashes occurring on weekdays, but there were higher crash rates on weekends. This same pattern held true for rates of fatal crashes. One of the reasons for these patterns was that most of the travel on weekends is recreational compared to on weekdays, which is primarily work related. More recently, Hijar et al. (2000) confirmed that the reason for travel was a factor in crash occurrence. This implies that a lower portion of the crash occurrence can be explained by reason for travel relative to that of day of the week. Because work-related travel and recreational travel are not exclusive to just weekdays and weekends, respectively, there is some overlap that can cloud some of the relationship between the 2 categories. Yau (2004) found day of the week to be an important factor affecting severity of injury. Another study by Vorko-Jović et al. (2006) analyzed the risk factors for traffic crashes in the city of Zagreb, Croatia, and their results revealed that weekends were a factor. Though these studies defined the working weekdays as Monday–Thursday and the weekends as Friday–Sunday, Valent et al. (2002) used Monday–Friday as the working week, with Saturday in its own category, and then used Sundays and holidays together in a separate category for Udine, Italy. Thus, the day of the week does indeed have an impact on the likelihood of a crash occurring. The significance of the impact is determined by the type and number of other risk factors that are associated with the model in question. Additionally, several studies have identified the critical role of weather-related vision hazards on fatal motor vehicle crashes (Abdel-Aty et al. 2011; Ashley et al. 2015; Khan et al. 2008; Pisano et al. 2008).

Though the above-mentioned factors have been thoroughly examined regarding the impact of each risk factor in the cause of a traffic crash, there are a limited number of studies examining the spatial distribution of crashes. For instance, Ashley et al. (2015) found a spatial clustering of these crashes in the eastern half of the United States due to weather-related vision hazards. Furthermore, Zegeer et al. (2008) analyzed the spatial distribution of crashes involving pedestrians within Miami–Dade County from 1996 to 2001. The purpose was to analyze the age distribution of the victims. Their study consisted of the results of a project implemented for a pedestrian safety program documented from 2002 to 2004. Their results showed that pedestrian crash rates decreased by 8.5 to 13.3% countywide during the peak of the program, which was 2003–2004. However, there is limited analysis of the spatial distribution of car-to-car crashes within Miami–Dade County and the prevailing risk factors that may have led to the crash. Understanding the spatial distribution of crashes in relation to different factors is important for identifying hot spots. The results of this study would thus help improve conditions of the areas prone to crashes and make them safer places to drive. Therefore, the objective of this study is to analyze the spatial distribution of the vehicles involved in crashes in Miami–Dade County (Figure 1). In addition, we analyzed the role that time of day, day of the week, seasonality, and driver age play in the distribution of traffic crashes.

Methods

The study area is Miami–Dade County. However, because a large portion of the county is uninhabited, the study area was reduced to the part of the county that lies within the urban development boundary. There are very few developments beyond the urban development boundary, which constitutes the portion of the Everglades that lie within the county (Labiosa et al. 2010). A major share of Miami–Dade County’s economy is from tourism. As of 2015, Miami ranked number one in the nation in hotel markets, visitor occupancy, and most expensive average room rates (Brandt 2015; Vianna 2015). It also has a large percentage of senior citizens. According to the 2010 U.S. Census, 14.1% of Miami–Dade County’s population was aged 65 or older (Miami–Dade County Department of Planning and Zoning 2011). There are also those 65 and over who travel to the Miami area in the winter to escape colder weather in the

Figure 1. Miami–Dade County with the urban development boundary.
north, commonly referred to as "snowbirds." Additionally, winter (which includes the months of December to April) is the peak travel season for Miami–Dade County with the snowbirds and the tourists.

The Florida Department of Transportation provided crash data on all reported crashes within Miami–Dade County from 2005 to 2010. At the time this study was conducted, these were the most recent data available. These data were compiled into 2 groups: on the system and off the system. On the system refers to crashes that occurred on a freeway or a state road, and off the system refers to crashes that occurred on secondary and side streets. In this study, only off-the-system crashes were used because those crash dynamics are more spatially sensitive to the categorical breakdowns and also are not restricted to only interstates and state highways, thus covering a more expansive and complete area of the study area. Every crash recorded has information about the crash, including its date, time, location, weather conditions, road conditions, visibility, crash lane, and road surface type. There is a second data set that contains additional information about the occupants involved. This data set lists the same crashes but contains information on whether the victim was the driver, an occupant, or a pedestrian. Other information includes age, whether alcohol was an influence, whether there was an ejection, whether a safety belt was used, and whether there was an injury and whether that injury was fatal.

The data were split into different categories based upon the following criteria (Table 1):

- If the crash was fatal, at least one person died in the crash.
- The day of the week (whether the crash occurred on the weekday or the weekend).
- The crashes that occurred during the morning and evening rush hours (on weekdays only).
- The time of year in which the crashes occurred (peak travel season and low travel season).
- The age of the people involved (<25, 25–34, 35–44, 45–54, 55–64, 65+).

The day of the week and time of the year groupings were used as representations for reason for travel; for example, work versus recreational use. The day of the week groupings were split into weekday and weekend occurrences. The weekday is defined as Monday through Thursday, and the weekend is defined as Friday through Sunday, based upon how the literature classified the weekdays and weekends (Table 1).

In order to examine the overall spatial patterns of traffic crashes in Miami–Dade County, a nearest neighbor analysis was executed. The nearest neighbor index, a global statistic for analyzing distribution, is used to indicate whether or not there is a general clustering of events. The nearest neighbor index is a common method of measuring the pattern of feature locations, in this case the vehicular crashes. The nearest neighbor index measures how similar the mean distance between each vehicular crash location and its closest vehicular crash location is to the expected mean distance for a hypothetical random distribution of vehicular crashes. The index, expressed as the ratio of observed to expected mean distances, indicates whether or not there is general clustering of vehicular crash incidents and the corresponding z-score and probability values test the significance of clustering. The nearest neighbor index has been found to be useful when analyzing data that are distributed along a line (Mitchell 2009). It is therefore considered a suitable statistic for studying the pattern of vehicular crashes which occur along linear road features.

Though global statistics indicate the presence or absence of general clustering in the study area, hotspot analysis helps identify a location or a small area within an identifiable boundary showing localized concentration or clustering of incidents (Getis and Ord 1992; Ord and Getis 1995). The Getis-Ord Gi* statistic is used to identify the hot spots, also known as "blackspots" (Elvik 2007; Park et al. 2014), of vehicular crashes within the study area. The Getis-Ord Gi* is a neighborhood-based statistic that identifies hot and cold spots by considering each vehicular crash within the context of all vehicular crashes in the neighborhood and determining whether and how the local pattern of crashes in the neighborhood is statistically different from the global pattern of mortality in the entire study area. The Gi* statistics is actually a z-score. Statistically significant high Gi* values indicate clustering or the presence of hot spots, with the highest Gi* or z-score values indicating the most intense clustering or the hottest spots of vehicular crashes.

Cold spots are similar, except that they are the clusters of the statistically significantly lowest scores, which show the areas of the lowest crash occurrence. Finally, a simple kernel density analysis was executed to reveal the age-wise spatial variation of traffic crashes. These methods have been successfully applied in previous analyses of road crashes (Erdogan et al. 2008; Goodwin et al. 2014; Prasannakumar et al. 2011; Xie and Yan 2013).

**Results**

The results of nearest neighbor analysis for all off-the-system crash data showed significant spatial clustering for all categories at the 99% confidence level in Miami–Dade County. Therefore, in order to identify the spatial patterns of clustering of crashes across Miami–Dade County for the various subcategories of traffic crashes (Table 1), a hotspot analysis was conducted.

**Fatal crashes**

The results of the hotspot analysis for off-the-system fatal crashes showed a clustering in Little Haiti, Homestead, Tamarind, the western portion of Doral, Key Biscayne, and Virginia Key, which are predominantly residential areas (Table 2). The cold spots were located in Aventura all the way south through Miami Beach, Coconut Grove, the Port of Miami, and Cutler Bay, which tend to be commercial and entertainment areas that have lower speed limits (Figure 2).
Table 2. Characteristics of cities of note within Miami–Dade County.

| City         | Characteristics |
|--------------|-----------------|
| Aventura     | Residential     |
|              | Wealthy         |
| Bal Harbour  | Residential     |
| Coconut Grove| Upper income    |
|              | Residential     |
|              | Middle income   |
|              | Bars            |
| Coral Gables | Residential     |
|              | Students        |
|              | Bars            |
| Cutler Bay   | Middle income   |
| Doral        | Residential     |
| Downtown     | Middle income   |
| Hialeah      | Residential     |
| Kendall      | Lower income    |
| Kendal Biscaye| Residential     |
| Key Biscayne | Upper income    |
| Miami Beach  | Residential     |
|              | Commercial      |
|              | Tourists        |
|              | Bars            |
| Sunny Isles  | Residential     |
| Tamiami      | Upper income    |
|              | Residential     |
|              | Middle income   |

**Weekday and weekend crashes**

The hotspots for weekdays were located in downtown Miami, West Miami, Hialeah, Doral, and Miami Beach. The cold spots (areas of low clustering of crashes) were located in Surfside north through Aventura, Country Club, Kendall and West Kendall, and Cutler Bay (Figure 3). The hotspots and cold spots for weekends were located in the same areas as they were for the weekdays, with the exception that the Port of Miami was also a hotspot (Appendix Figure 1, see online supplement). Doral and Hialeah are large residential areas with daily commuters to work. Downtown Miami was an obvious hotspot, due to the higher concentration of offices, whereas Miami Beach and West Miami are well-known tourist attraction centers. These are areas that provide a host of recreational experiences such as beaches, malls, food, and access to alcohol. The fact that the cold spots intensify on the weekends compared to the hotspots suggests that people drive less in those areas of clustering of negative z-scores on the weekends relative to the weekdays.

**Morning and evening rush hour crashes**

The crashes that occurred only on weekdays were then classified into morning rush hours (6:30 a.m.–9:30 a.m.) and evening rush hours (3:30 p.m.–7:30 p.m.). The morning rush hour hotspots were located in downtown Miami, Coral Gables, and in Doral. The cold spots were in Aventura south through Bal Harbour, Country Club, Kendall, and West Kendall (Figure 4). The evening hotspots were also concentrated in downtown Miami, Coral Gables, and Doral, in addition to Hialeah and Miami Beach (Appendix Figure 2, see online supplement). This could be “happy hour traffic,” which implies people getting off from work and going to the beach for happy hour specials.
Hialeah hotspot can be because of a large number of people driving to get home from work. The crashes are prominent along Okeechobee Road, which is a diagonal road in a dominantly north–south–east–west grid. Thus, roadway geometry may be a relevant factor in this area. The Port of Miami becomes a hotspot on weekends because the cruise tours are more active on the weekends than on the weekdays.

**Low and peak travel season crashes**

The time of the year is also important to investigate in view of the dominant tourist economy and the out-of-state snowbird influx during winter. The analysis were conducted for peak (January to May) and low travel seasons (June to September). The hotspots in the low travel season were located in downtown Miami, West Miami, Coral Gables, Doral, Hialeah, and Miami Beach. The cold spots were located in Aventura south into Mid-Beach, Miami Shores, Country Club, Kendall and West Kendall, and Cutler Bay (Figure 5). In the peak travel season, the hotspots and cold spots were located in the same areas as the low travel season. The hotspots in Hialeah and Doral were less prominent in the peak travel season than they were in the low travel season. Coconut Grove is more intense during the peak travel season, due to various art shows and other activities that attract a large number of people to this area (Appendix Figure 4, see online supplement). The lack of a stark contrast in the spatial patterns between the low and peak travel seasons supports the fact that even though Miami still has a largely tourism-based economy, the role of tourism has declined in recent years. The winter months are still the peak season, but the peak is not nearly as pronounced as it used to be (city-data.com 2009).

**Age-wise crashes**

On the basis of age, the results of the kernel density show that there was a consistent clustering located in downtown Miami, Miami Beach, and Coral Gables for all age groups (Appendix Figure 4, see online supplement). With an increase in age, there is a shift in the pattern to where those who are 65 and older are starting to have a higher clustering in the inland areas of Hialeah and Aventura. The crashes involving all age groups, except those 65 and above, were concentrated in Downtown Miami, Miami Beach, Little Havana, and Coral Gables. These 3 areas in particular are entertainment centers that contain bars and nighttime entertainment. For the 35 to 44 year age group, Hialeah shows up as an area of relatively greater crash density. In the case of the 55 to 64 year age group the crash density expands northward toward Aventura. The crash densities for 65 and older exhibit the pattern with the greatest difference compared to all other categories. The higher density of crashes is spread over not only South Beach and Downtown Miami but also across Coral Gables, Hialeah, and Aventura. This wider spread is because these are areas that have a relatively higher density of retiree population. Additional analysis was conducted on the age group 80+. However, there were no significant differences in the distribution of 80+ from 65+.

**Discussion**

Although the importance of factors such as alcohol, driver age, time of day, day of the week, and time of the year are well
documented in several studies, these factors have not been explored spatially. In this study we address those gaps by exploring the spatial significance of these risk factors and understand how the distributions of crashes change with respect to where the fatal crashes occur, the age of the driver, time of day, day of the week, and time of the year.

- Fatal crashes were more concentrated in residential areas, whereas the cold spots were concentrated in entertainment areas that contained slower speed limits. These were areas where one could expect to find many tourists on foot.
- The distributions of crashes that occurred on weekends do not vary much. However, the intensification of the cold spots on weekends can be attributed to fewer people driving during the weekends. The cold spots were located in residential areas and the hotspots are located in areas that provide recreational experiences. On weekends, less people drove in the residential areas, whereas more people drove in the recreational areas. A lower density of drivers on the road in the residential areas intensified the cold spots. On the other hand, no reduction in density of drivers in the recreational areas did not result in any substantial changes in the intensity of the hotspots.
- Travel seasonality does not play a significant role in the traffic crash pattern. The lack of variability in the distributions of the spatial patterns of crashes in the low and peak travel seasons helps support the notion that Miami’s primarily tourism-based economy is becoming more year-round. Both seasons have the same distribution, which suggests that the areas are seeing the same type of popularity, no matter the time of year.
- With an increase in age, the spatial clustering of traffic crashes migrated to the residential areas from the dominant entertainment areas (Appendix Figures 4A–4F).

The results of the analyses above enable us to further understand the spatial patterns of crashes within Miami–Dade County, with respect to time of day, week, and year. We wanted to highlight the consistency of the hotspots and cold spots. However, closer examination will reveal the relative shifts for the different comparisons made within this study. The overall patterns that are similar highlight the most crash-prone areas, but the change in intensity will highlight how the highest risk areas change within the scope of comparison. Many of the areas that consistently appeared as hotspots were the entertainment districts of Miracle Mile in Coral Gables, the Brickell Financial District of Downtown Miami, along with South Beach in Miami Beach. These areas were especially popular with the <25 age demographic. This finding agrees with the conclusion made by Goodwin et al. (2014) when studying the crashes in Houston, Texas. Many of the hotspots in were popular locations for young adults, such as the central business district, areas of bars, clubs, and special event centers. However, when time of day is taken into account, Cela et al. (2013) found that most crashes in Serbia occurred between 10:00 a.m. and 4:00 p.m., whereas in this study in Miami, most crashes occurred between 6:30 a.m. and 9:30 a.m. and 3:30 pm and 7:30 p.m.

The results of this study will help in the formulation of more effective measures to identify the most vulnerable areas within a tourism-based city to help reduce the number of crashes and the number of fatalities. The results show that there are numerous other, more localized factors that may play a significant role in the final spatial patterns. Some measures might include reducing the amount of time that a major streets light is red in order to reduce traffic backup or turning a 3-way intersection into a roundabout. The scope of this study expands beyond Miami, due to some of the typical characteristics similar to other major American cities. For instance, Miami is experiencing rapid gentrification, like Inglewood, California (Kaplan 2015) and has a segregated population dynamic like Atlanta, Georgia (Thompson 2000), and urban sprawl like Phoenix, Arizona (Bernstein et al. 2014; Ewing et al. 2003; Tian and Wu 2015). Gentrification and population class segregation can contribute to crashes because there is a higher risk of crashes in lower income neighborhoods (Aguerro-Valverde and Jovanis 2006; Morency et al. 2012). In addition, when gentrifying an area, there is substantial construction in the area, which can also be a factor in causing more crashes (Hijar et al. 2000). Urban sprawl creates a lot of residential areas on the outskirts of the region, which can be hot zones for crashes, as we have seen in this article. Therefore, the findings of this study are relevant beyond Miami–Dade County.

For future work, we suggest doing this type of analysis in other geographic areas and within different cities to analyze their distribution patterns for comparative analysis. Another study could be one that focuses only on the age demographic of 65+ and then separating differing age groups within that demographic. This is because of the higher proportion and risks involved with this age group. If there are medical causes for some of these crashes, these can then be analyzed and their distributions can be mapped from there. Future studies may include a more detailed analysis of the role of prevailing weather conditions and proximity to educational facilities on the distribution traffic crashes. Furthermore, another study could be that of analyzing the testing density of traffic within the residential areas and entertainment/recreational districts on weekdays and weekends, along with other factors that were not included in this study, such as traffic lights and speed limits.

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