Received 19 May 2023
Revised 24 September 2023
Accepted 27 September 2023

Does Weisburd's law of crime concentration apply to traffic crashes? Implications for policing and traffic law enforcement

Sangjun Park
Southern Utah University, Cedar City, Utah, USA, and
Cynthia Lum
George Mason University,
Fairfax, Virginia, USA

Abstract

Purpose – A considerable amount of police evaluation research focuses on innovative approaches to reduce crime at places. This is hardly coincidental; policing and place-based scholars have found crime is highly concentrated, and when police focus on these places, they can prevent and reduce crime. The regularity of such findings led Weisburd (2015) to assert the existence of a "law of crime concentration." Given that bold assertion, the authors test whether the law of crime concentration is generalizable to one of the most common public safety concerns that police handle—traffic crashes.

Design/methodology/approach – To determine whether the law of crime concentration applies to traffic crashes, the authors examined crash locations and times in all counties in Utah across four years. Following and expanding on Weisburd's methods, the authors calculate the bandwidth of concentration for these crashes and analyze various types by severity and possible explanations for variations in crash concentrations across the state.

Findings – A small proportion of street segments and intersections experience a disproportionately high number of crashes, and the degree of concentration of crashes may be even higher than that of crime. Further, there are variations in the levels of crash concentration across counties and in the severity of injuries resulting from the crashes.

Practical implications – Place-based criminologists and policing scholars have not often explored traffic crashes in their analyses. Yet, traffic problems take up a significant amount of law enforcement time and resources and are often priorities for most law enforcement agencies. Given what the authors know from traffic, policing and crime and place research, targeted approaches at micro traffic crash hot spots can be beneficial for public safety prevention.

Originality/value – This study is the first to explore the application of Weisburd's Law of Crime Concentration to traffic crashes. Given that police spend a significant amount of time and resources on traffic-related problems in their jurisdiction, finding more effective, evidence-based approaches to address this public safety concern should be a high priority for police and researchers alike.

Keywords Evidence-based policing, Crash prevention, Crime concentration, Environmental criminology, Traffic crashes, Traffic law enforcement, Hot spots

Paper type Research paper

Introduction

A great deal of police evaluation research focuses on innovative approaches to reduce crime at places. This is hardly coincidental, as there is a substantial overlap between policing and

Policing: An International Journal
Vol. 46 No. 5/6, 2023
pp. 922-940
Emerald Publishing Limited
1363-951X
DOI 10.1108/PIJPSM-05-2023-0062

place-based scholarship, crime prevention and crime analysis. Place-based and environmental criminologists continue to find that crime concentrates geographically at specific "micro" locations, and when the police focus on these places, they can effectively reduce crime. The regularity of these findings led Weisburd (2015) to declare the concentration of crime so common that it can be considered a "law."

Assertions of laws or general theories are rare in criminology and naturally prompt questions about their universality and application to various public safety issues that communities face. One significant public safety concern much less explored in crime, place and policing research is traffic accidents and crashes. Traffic problems are a significant part of how the police spend their time and resources. Does the law of crime concentration generalize to traffic crashes? Are traffic crashes similarly and highly concentrated at micro places such that most traffic crashes occur with a very small proportion of street segments? If so, does this also mean that place-based theories and interventions applied in policing to those micro places are also relevant to traffic problems?

In this study, we are the first to explore the generalizability of Weisburd's Law of Crime Concentration to traffic crashes. We do so by analyzing all crashes in every county in Utah and calculating crash concentration in similar ways as Weisburd for each jurisdiction. If the law is applicable, the implications for preventing traffic crashes are significant, given what traffic scholars have already discovered about causes and interventions for crashes and fatalities and what we know about policing and public safety prevention more generally.

The law of crime concentration and traffic crashes

Scholars of policing, environmental criminology, and crime and place have continued to build strong theoretical and empirical support for a simple but powerful generalization: crime and disorder concentrate geographically at specific locations (see Eck *et al.*, 2007; Groff *et al.*, 2010; Johnson and Bowers, 2004; Madensen and Eck, 2008; Park and Lum, 2021; Sherman *et al.*, 1989; Smith *et al.*, 2000; Weisburd and Eck, 2018; Weisburd *et al.*, 2004; Weisburd *et al.*, 2012, 2016; Wikström *et al.*, 2012). Moreover, even within seemingly socioeconomically homogenous neighborhoods or communities, crime patterns exhibit high levels of street-by-street variations (see Gill *et al.*, 2017; Hibdon, 2013; Sherman *et al.*, 1989; Weisburd and Amram, 2014; Weisburd and Green, 1995; Weisburd *et al.*, 2004, 2009, 2012, 2016; Wheeler *et al.*, 2016). Studies have also shown that these micro-geographic concentrations of crime are likely stable over many years (Andresen *et al.*, 2017; Curman *et al.*, 2015; Groff *et al.*, 2010; Weisburd *et al.*, 2004).

This corpus of research led Weisburd (2015) to assert in his Sutherland Address for the American Society of Criminology the existence of a "Law of Crime Concentration." He noted that study after study has shown that crime tends to concentrate "within a narrow bandwidth of percentages for a defined cumulative proportion of crime" (p. 132). He found that when reverse ranking street segments from those with the most to the least crime (see Sherman *et al.*, 1989), about 50% of crime was concentrated in just 4.2–6% of larger cities' highest crime street segments. He also confirmed the preliminary finding by Hibdon (2013) that crime might be even more concentrated in less-populated cities he examined. Between 2.1 and 3.5% of street segments held 50% of crime at street segments in less populated places. These findings have also not been limited to the United States, suggesting the law holds in other countries (see, e.g. Curman *et al.*, 2015, in Vancouver; Weisburd and Amram, 2014, in Tel Aviv-Jaffa; Jaitman and Ajzenman, 2016, in five Latin American cities; Park and Lum, 2021, in all cities, towns and counties in the England and Wales) [1].

Environmental and crime and place scholars posit that the reasons for these concentrations—especially at very specific locations even within seemingly socioeconomically homogenous communities—are likely a combination of intersecting routines activities, environmental factors and physical structures at those places that create opportunities for crime (Brantingham and Brantingham, 1993; Eck *et al.*, 2007; Sherman *et al.*, 1989; Weisburd *et al.*, 2012, 2016). Something about *this* intersection seems to draw crime and disorder to it, rather than *that* intersection two blocks away. Such research goes hand-in-hand with evaluation studies that have found that when communities and law enforcement agencies target these crime and disorder concentrations at specific places with problem-solving, proactive or community-oriented interventions, they can reduce and prevent crime at those locations (for reviews of this research, see Braga *et al.*, 2019; Lum and Koper, 2017; National Research Council, 2004; National Academies of Sciences, 2018).

Assertions of laws and generalized theory are rare in criminology and naturally prompt questions about their universality and generalizability. The crime concentration research has focused almost exclusively on crime (e.g. violence, property crime, thefts, frauds) and disorders (e.g. vice, public intoxication, noise, graffiti, minor juvenile delinquency). However, one significant public safety concern often ignored in this research (and policing studies more generally) has been traffic crashes and fatalities (including those involving pedestrians). This omission is unwarranted for several reasons. According to the CDC, traffic crashes are the leading cause of death in the United States for people under 55 [2] and a significant public safety concern, particularly after the COVID-19 pandemic [3]. Traffic-related concerns are one of the most frequent types of 911 calls for service from citizens that the police receive. Examining computer-aided dispatch data from nine police agencies, Lum *et al.* (2022) found that traffic-related calls for service averaged 17% of all calls and could be as high as a quarter of all calls in some agencies. To put this in perspective, traffic calls to the police are, on average, 13 times more frequent than calls related to mental health concerns, three times more than calls for violence and 1.6 times more than calls related to property offenses. Traffic enforcement is also one of the most common activities that uniformed patrol officers proactively engage in when not responding to 911 calls (see Lum *et al.*, 2020). In total, a large portion of public safety expenditures are devoted to responding to traffic problems or enforcing traffic safety laws.

Extensive transportation research has already found that traffic accidents and crashes occur more frequently in certain places and times and has also explored the behavioral routines and environmental causes and correlates of traffic crashes. Some of these studies focus on larger place and time units, such as higher-density city centers (Alkhadour *et al.*, 2021; Dezman *et al.*, 2016; Rahman *et al.*, 2020; Zhang *et al.*, 2022) or during congested traffic hours (Li *et al.*, 2020; Plug *et al.*, 2011; Zhang *et al.*, 2022). However, a large body of transportation research examines specific behavioral and environmental factors contributing to crashes. This corpus of knowledge is too large to do justice to here, but several meta-analyses illuminate this point. Behavioral factors contributing to crashes have included speeding and aggressive driving (NHTSA, 2022; Su *et al.*, 2023), impaired driving (Elvik, 2013), sleepiness (Bioulac *et al.*, 2017), poor decisions and distracted driving (Shaaban and Ibrahim, 2021), texting (Caird *et al.*, 2014), lack of familiarity with the location (Intini *et al.*, 2019) and other errors (e.g. de Winter and Dodou, 2010). Environmental factors such as road conditions (Høye and Hesjevoll, 2020), weather (e.g. Saha *et al.*, 2016), lighting (Elvik, 1995), signage (Fisher *et al.*, 2021a, b) or the presence of road calming interventions (Elvik, 2001) also can increase (or decrease) the probability of crashes at specific locations. Scholars have also explored the complex interactions between these behavioral and environmental factors (e.g. Alarifi *et al.*, 2018; Bassani *et al.*, 2020; Cai *et al.*, 2018; Castro *et al.*, 2012; Wang *et al.*, 2017).

Traffic studies in many ways mirror the crime concentration (and intervention) scholarship in criminology and policing. The research supporting the law of crime concentration also indicates that "everyday" behaviors and environmental conditions contribute to crime occurring at specific places (Felson and Boba Santos, 2009). Given these theoretical parallels, we might hypothesize that traffic crashes spatially concentrate similarly to crime. Some research behind the Data-Driven Approaches to Crime and Traffic Safety "DDACTS" program supports this possibility (with caveats—see Wu and Lum, 2019; Wu *et al.*, 2021). DDACTS was developed by a partnership between the National Highway Traffic Safety Administration (NHTSA) and components of the Department of Justice and implemented in several communities starting in 2008 (Cournoyer, 2011; NHTSA, 2013, 2014). Underpinning DDACTS was the theoretical proposition that those involved in traffic violations and crashes may also be more likely to be involved in crime and disorder (Michalowski, 1975) and that hot spots of traffic crashes also tended to be hot locations for crime (Carter and Piza, 2018; Giacopassi and Forde, 2000; Kuo *et al.*, 2013; Stuster, 2001). The idea behind DDACTs was that analysis could show the co-location of crime and traffic incidents, which might justify highly visible traffic enforcement initiatives that could combat both (Burch and Geraci, 2009). We do not discuss the merits (and challenges) of the DDACTS program here, but note the parallels others have tried to make between the geographic patterning of crime and traffic accidents in the context of the generalizability of the law of crime concentrations.

On the other hand, driving is ubiquitous, and the number of possible road segments and intersections in which a crash could occur could be argued as much more extensive than places where crime could happen. Perhaps intersecting behavioral and environmental factors are less spatially discerning (or more widespread) than the opportunities leading to crime and disorder. For example, while traffic accidents and crashes might occur at certain places, perhaps that concentration is lower than that of crime (e.g. instead of 50% crashes in 5% of all segments and intersections, they are in 20%). This leads us to the question of this inquiry: Would the law of crime concentration also apply to traffic crashes?

Data and method

To explore this question, we examined all crashes within each of the 29 counties in Utah, [4] where traffic crashes and fatalities have been a significant concern. Between 2019 and 2021, fatalities involving vehicles, motorcyclists and pedestrians increased, only slightly declining in 2022 [5]. As with many states, a significant portion of Utah's public safety budget focuses on traffic safety. In the first quarter of 2023 (at the time of writing), the US Department of Transportation had invested $3.2m in funds for six road safety projects in Utah (Williams, 2023a). Utah also contains many small towns and rural areas. As NHTSA's National Center for Statistics and Analysis (NCSA) has reported, rural locales often have higher crash fatalities per capita than their urban counterparts, and Utah is no exception (NCSA, 2022; see also Hasson, 1999). Traffic safety concerns have prompted several communities and leaders in Utah to call for more attention to reducing vehicle crashes (see, e.g. Bree, 2022; Park, 2022; Williams, 2023b).

We examine crashes across an entire state because doing so allows us to test Weisburd's law in heterogeneous jurisdictions that fall under similar traffic laws and mandates. Weisburd's law (as applied to traffic crashes) would assert that the narrow bandwidth of concentration would apply to different types of jurisdictions (i.e. suburban, urban, rural and mixed-use communities), with different levels of traffic crashes and severity of crashes, and consistently from year to year. Appendix 1 displays several characteristics of each of the 29 counties in Utah, showing high variations in population density, numbers of street segments and intersections, crash frequencies at both street segments and intersections, and median length of street segments. As such, Utah's 29 counties vary significantly in geography and demographics, providing an excellent opportunity to examine the generalizability and application of Weisburd's law to traffic crashes.

This study uses Utah's Department of Transportation (UDOT) crash data from its Traffic and Safety Division to calculate the concentrations of crashes in each county in the state [6].

This data provides the precise location of each recorded crash (latitude and longitudinal coordinates); the factors that contributed to each crash and injury (e.g. drunk driving, teenage driver involved, night dark condition or not wearing a seatbelt); and the severity of the injury resulting from each crash. We group crashes into three categories for our analysis: (1) all crashes, (2) low-severity injury crashes (LSI) and (3) high-severity injury crashes (HSI). LSI crashes include those with no injury, possible injury or suspected minor injury. HSI crashes include events where a severe injury or fatality was recorded. In addition, we examine four (rather than one) years of crash data to determine if concentration levels are stable across multiple years. We chose the most recent years in which data were available that would not be impacted by the significant disruption in driving routines brought on by the COVID-19 lockdowns of 2020 and 2021. In total, we included 252,485 crashes from 2016 to 2019 for our analysis [7].

Like Weisburd, we calculate crash concentrations at street segments created using arcs in a geographic information system [8]. These arcs are portions of streets or roads separated by intersecting streets. Highways or interstates were segmented by ramps, exits or other merge points. However, we also separately calculate the concentration of crashes at intersections, given that many occur at intersections. To determine the number of traffic crashes at every street segment and intersection in Utah, we geocoded [9] each crash location to the street segment or intersection where it occurred, using street networks provided by the Utah Geospatial Resource Center.[10] The crash data was very mappable; only 15 crashes could not be geocoded for this analysis.

We summed the total number of events at each street segment or intersection and ranked the segments and intersections from most to least crashes. We then calculated the cumulative percentage of crashes in that ranking (a calculation initially developed by Sherman *et al.*, 1989). This cumulative percentage then allowed us to calculate what proportion of intersections or segments held 25%, 50%, 75% and 100% of all crashes for each of the 29 counties and each year examined. We repeated these calculations for LSI and HSI crashes to determine if the law of crash concentrations also holds for minor and more severe crashes.

Results

Overall concentrations for all crashes

Table 1 shows, for all crashes, the average percentage of street segments or intersections in which each proportion of crashes is concentrated across the 29 Utah counties (see Appendix 2 in the supplemental material for the specific concentrations for each Utah county from which this table derives). The minimum and maximum percentages reveal the range of these concentrations across the 29 counties. Counterintuitively, the minimum percentage reflects the "highest" or "tightest" concentration (crashes are within that percentage of segments or intersections), and the maximum percentage reflects the opposite (the county in which traffic crashes are the most dispersed—albeit still very concentrated).

Table 1. Average crash concentration calculations for 25%, 50%, 75% and 100% of all crashes across 29 Utah counties (2016–2019)

	Percentage of street segments				Percentage of intersections			
% Of all crashes	M (%)	SD (%)	Min (%)	Max (%)	M (%)	SD (%)	Min (%)	Max (%)
25%	0.14	0.08	0.02	0.36	0.17	0.11	0.04	0.46
50%	0.52	0.30	0.06	1.15	0.56	0.37	0.10	1.42
75%	1.70	1.06	0.25	4.03	1.56	1.18	0.21	4.02
100%	6.88	5.50	1.33	22.91	5.53	6.59	0.25	23.73

Note(s): M = mean. SD = standard deviation
Source(s): Table by authors

Table 1 reveals four provocative findings. First, on average, crashes are incredibly concentrated in Utah. *All* crashes (100%) in the state's counties from 2016 to 2019 occurred in just 6.9% of the street segments in Utah and 5.5% of street intersections. This concentration is especially evident when examining 75% of total crashes: the vast majority of crashes in Utah occur in less than 2% of the entire state's street segments and intersections. Second, Table 1 illustrates that Weisburd's law generally applies to traffic crashes. The bandwidth of concentrations across the 29 counties, reflected in the minimum and maximum values, is fairly narrow, except when examining 100% of all crashes. For example, using Weisburd's (2015) and Sherman *et al.*'s (1989) "50%" threshold, concentrations range from 50% of crashes occurring in 0.06–1.15% of street segments and between 0.10 and 1.42% of all intersections. The bandwidth for 75% of all crashes is 0.25–4.03% of street segments and 0.21–4.02% of intersections. To put this into perspective, in Beaver County, 75% of all of its crashes between 2016 and 2019 can be linked to just 20 street segments and 28 intersections. Third, these concentrations also appear stable over the four years (more on this later). And fourth (and most interesting), these stable concentration levels appear *even more* concentrated than Weisburd's crime concentration findings. For example, if looking at 50% of crashes, our concentrations appear to be at least five times (if not many more times) more concentrated than crime, a hyper-concentration that persists over four years.

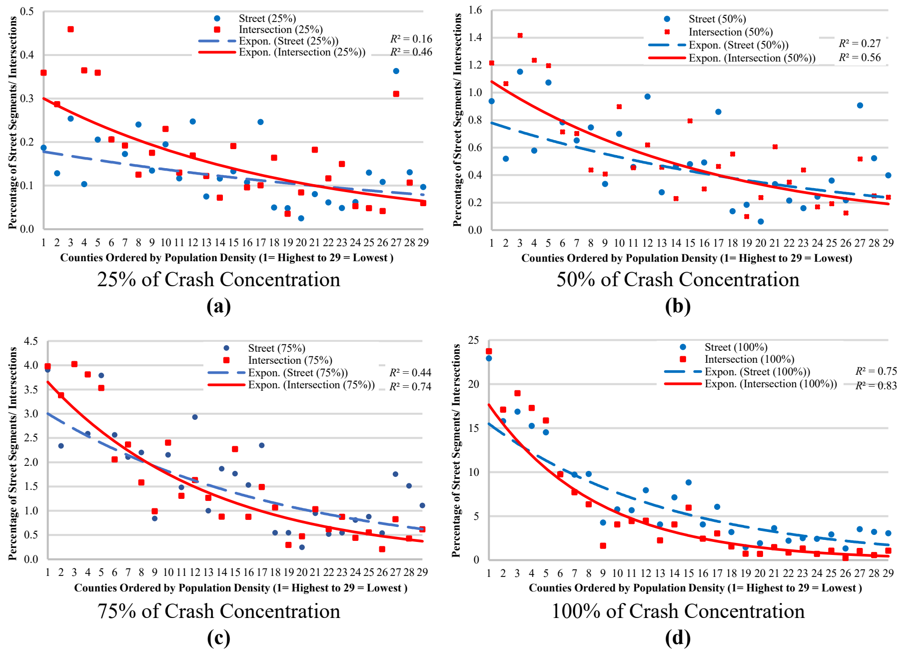
Whether a bandwidth of 0.06–1.15% for 50% of all crashes at street segments would be considered "narrow" is a debate already discussed by Park and Lum (2021). If traffic crashes are already naturally highly concentrated (which they are, even at the 100% threshold), "narrowness" may be relative. Perhaps of more practical importance is what might explain the variations that we see across counties. For our analysis here, we examine whether the population density of a county might predict differences in crash concentrations [11]. Figure 1(a-d) plots the concentrations (for 25, 50, 75 and 100%, respectively) of all crashes at streets and intersections against the overall population density of counties as denoted from highest population density (ranked "1") to lowest density (ranked "29"), from left to right. *R*-squared values in each graph represent the correlation between the levels of crash concentration and population density in a nonlinear regression model.

Figures 1c and 1d show higher *R*-squared values than Figures 1a and 1b, supporting the argument that population density can explain the variations of crash concentrations, especially when we use the 75% or 100% of all crashes threshold (R^2 = 0.61 for street segments and R^2 = 0.84 for street intersections) and 100% (R^2 = 0.86 for street segments and R^2 = 0.92 for street intersections) of crashes. At 25% or 50% of all crashes, correlations between concentration statistics and population density are lower but still substantial, especially for intersections. But overall, Figure 1 indicates that the less population dense a jurisdiction is, the *more* concentrated crashes are (i.e. more crashes are concentrated in an even smaller number of street segments and intersections).

Crash concentration by severity of injury

Additional insights are revealed about the spatial concentration of traffic crashes comparing traffic crashes by injury severity. Table 2 displays the average crash concentration calculations for LSI and HSI crashes for 25%, 50%, 75% and 100% of each type of crash at street segments and intersections across the 29 Utah counties (Appendix 3 provides the specific calculations for each of the 29 counties for LSI and HSI).

Table 2 shows the similarities between concentrations of all crashes and LSI crashes, given that LSI crashes constitute approximately 98% of all crashes in the dataset. However, HSI crashes are even more highly concentrated than LSI (and all) crashes. This may be due to HSI crashes (n = 5,652) being rarer than their LSI counterparts (n = 246,844). But even if they are rarer, this finding is interesting, given that other rare crime events (e.g. homicide) are



Source(s): Figure by authors

Figure 1.
Crash concentrations of 29 counties at street segments and street intersections plotted against County population density

Table 2.
Average crash concentration calculations for low-severity injury (LSI) and high-severity injury (HSI) crashes for 25%, 50%, 75% and 100% of all crashes at street segments and intersections across Utah's 29 counties

	Percentage of street segments				Percentage of intersections			
Crash	M (%)	SD (%)	Min (%)	Max (%)	M (%)	SD (%)	Min (%)	Max (%)
25% of . . .								
All crashes	0.14	0.08	0.02	0.36	0.17	0.11	0.04	0.46
LSI crashes	0.14	0.07	0.02	0.30	0.17	0.11	0.04	0.46
HSI crashes	0.08	0.04	0.02	0.18	0.08	0.07	0.01	0.26
50% of . . .								
All crashes	0.52	0.30	0.06	1.15	0.57	0.37	0.10	1.42
LSI crashes	0.51	0.30	0.06	1.15	0.56	0.37	0.08	1.42
HSI crashes	0.22	0.12	0.05	0.58	0.22	0.21	0.02	0.67
75% of . . .								
All crashes	1.70	1.06	0.25	4.03	1.56	1.18	0.21	4.02
LSI crashes	1.67	1.06	0.25	4.01	1.54	1.19	0.17	4.04
HSI crashes	0.44	0.25	0.14	0.98	0.40	0.43	0.04	1.43
100% of . . .								
All crashes	6.88	5.50	1.33	22.91	5.53	6.59	0.25	23.73
LSI crashes	6.71	5.47	1.30	22.74	5.44	6.54	0.21	23.51
HSI crashes	0.65	0.38	0.22	1.55	0.58	0.66	0.04	2.28

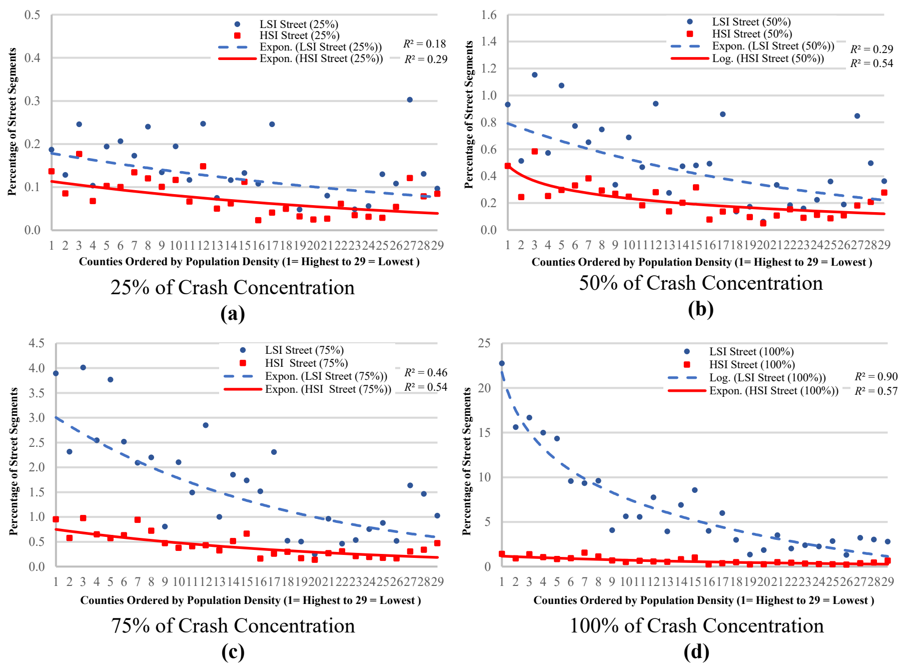
Note(s): M = mean. SD = standard deviation
Source(s): Table by authors

sometimes believed to be more distributed in space than more common events (e.g. auto thefts). For crashes, fatal events are more highly concentrated and, therefore, perhaps even more predictable than, for example, homicides. We return to this discussion later.

As with all crashes, population density may explain some of these patterns in LSI and HSI crashes. Figure 2 shows that the concentrations of LSI vary significantly across counties by different population densities at 75% and 100% concentrations compared to HSI (see Figures 2c and 2d). In counties with higher population density, LSI crashes have more proportions of street segments that hold 75% and 100% of crashes than counties with lower population density. Figure 2d shows this is especially true when considering all LSI crashes, not just the top 25% of high-crash segments. This was less the case with all HSI crashes, which did not seem as influenced by population density. This means relatively fewer street segments generated HSI across the counties, regardless of population density. The concentration of crashes with LSI and HSI on street intersections exhibits similar patterns as those on street segments (not shown).

Stability of crash concentration across time

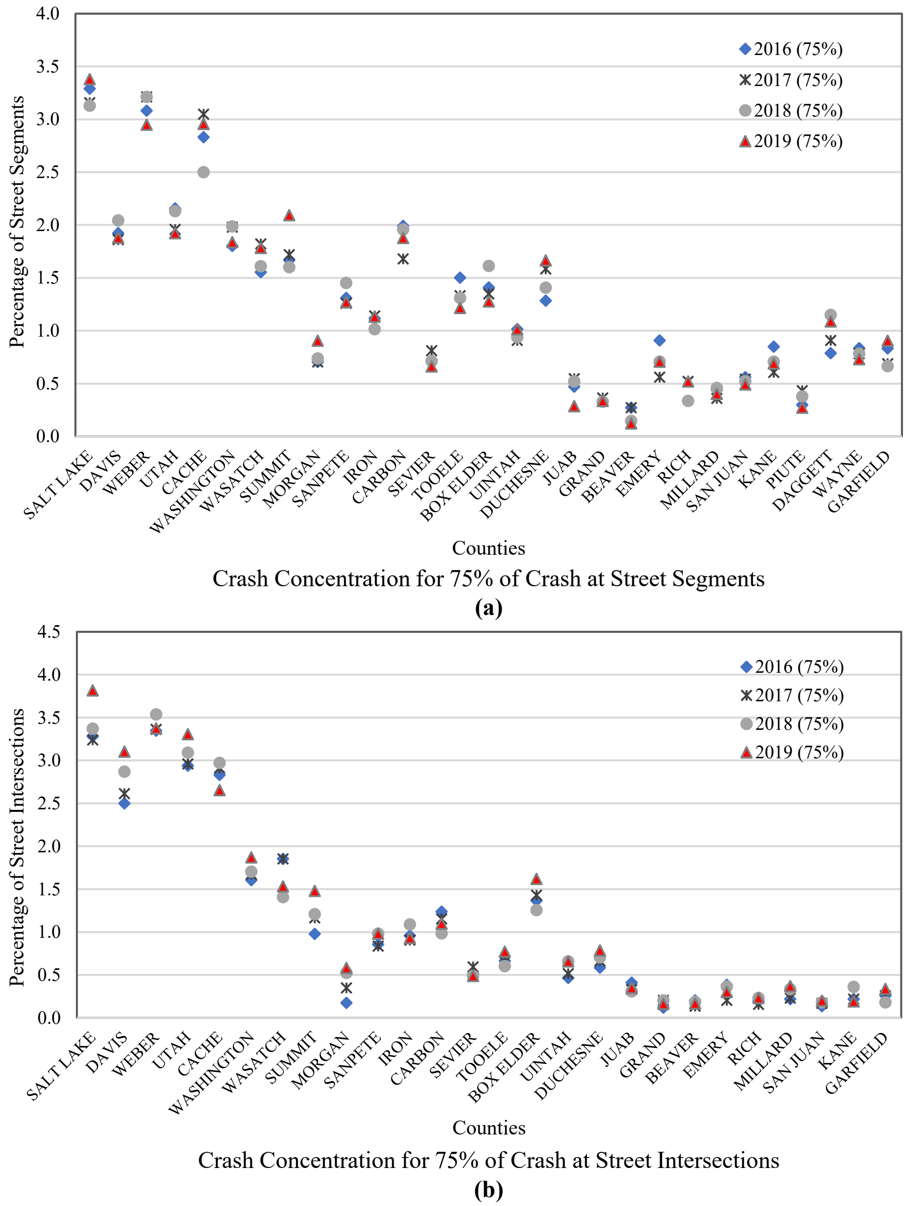
As with crime concentrations (see Weisburd *et al.*, 2004), places where crashes concentrate may be the same over time as they exhibit stable features that make them more prone to crashes. We emphasize that we do not replicate Weisburd *et al.'s* (2004) trajectory analysis here, and it is possible that the locations of the small proportion of street segments in which most crashes occur change from year to year. We calculated yearly crash concentrations for 25%, 50%, 75% and 100% across the 29 counties for 2016, 2017, 2018 and 2019 for street segments and intersections. While the data is too voluminous to display, we graphically show



Source(s): Figure by authors

Figure 2.
Crash concentrations of low-severity injury (LSI) and high-severity injury (HSI) crashes at street segments plotted by County population density

our calculations for 75% of all crashes at street segments and intersections in Figure 3 to emphasize our point (figures for 25, 50 and 100% of all crashes look similar) [12]. Figure 3 shows that the level of crash concentration remains stable (and highly correlated across jurisdictions) over the four years of data we collected for each county.



Source(s): Figure by authors

Figure 3.
Yearly (2016–2019) crash concentration for 75% of crashes at street segments and street intersections plotted for each Utah County ordered by highest to lowest population density

Discussion and practical applications

Our analysis confirms that Weisburd's law of crime concentration doesn't just apply to crime and disorder; the law may also apply to traffic crashes. While the variability in concentration (and the explanations for this variability) might make Weisburd's law more of an equation than a law (Park, 2019), the similarities are nonetheless striking. Indeed, traffic crashes may be even *more* highly concentrated than crime and disorder. Further, these concentrations appear stable over four years of traffic crash data.

These results are provocative for several reasons. Most practically, the police and other public safety groups working on traffic safety can identify the 1–2% of street segments or intersections (or less) in an entire county where most crashes will occur. In some counties in Utah, this might be 20 or fewer places. Targeting those places (or the routine activity journeys that lead to those crash sites—see Koper *et al.*, 2021) for traffic law enforcement and prevention activities would be the most efficient and strategic way for public safety agencies to expend their resources for this problem. As with crime, transportation scholars have extensively analyzed possible interventions to prevent and deter traffic accidents and crashes. Again, we will not do justice to that large body of literature here, but we point to several systematic reviews and evaluations of these interventions, from traffic calming approaches (Bunn *et al.*, 2003; Elvik, 2001), improving lighting (Elvik, 1995), licensing policies (Porchia *et al.*, 2014), speed cameras (Høye, 2014), road safety campaigns (Phillips *et al.*, 2011) and other deterrence-based approaches (see, e.g. Barnum and Nagin, 2021; Simpson *et al.*, 2020; Stanojević *et al.*, 2018), to name a few. Applying the evidence-base of traffic enforcement, prevention and deterrence, much more strategically and specifically to the small number of street segments and intersections where almost all crashes occur, seems like a straightforward solution.

.Unfortunately, the reality of implementing this solution may prove challenging. It is unclear whether most police agencies strategically and systematically target their traffic enforcement at places where traffic crashes concentrate. Lum *et al.* (2020) found that proactive patrol activities are often characterized by high levels of individual officer discretion, low supervision or guidance and are not driven by strategic intelligence. This is also true for traffic enforcement activities (Wu and Lum, 2019; Wu *et al.*, 2021). Additionally, the extensive evidence-base developed by transportation scholars is most likely not incorporated into academy, field or even specialized law enforcement training (Lum and Koper, 2017). Because of this reality of traffic prevention proactivity, it is also unclear whether policing, as practiced, has a measurable effect on mitigating highly predictable traffic crash concentrations. Further, the lack of strategic approaches to traffic crashes and the high levels of discretion in traffic enforcement may not only lead to prevention ineffectiveness but also to racial and ethnic disparities found in traffic stops, a problem well documented (see, e.g. Baumgartner *et al.*, 2018; Brown and Frank, 2005; Engel and Calnon, 2004; Fagan and Davies, 2000; Farrell and McDevitt, 2006; Lundman and Kaufman, 2003; Pierson *et al.*, 2020; Smith and Petrocelli, 2001).

Reducing the harms from traffic crashes *and* doing so without increasing the harms of disparity in police activity may require agencies to pay much sharper attention to the very specific and small number of locations we have identified in this study *and* think carefully about how to approach them using the evidence-base for traffic crash prevention that already exists. The differences in crash concentrations by population density and street segment length also indicate that analysis and approaches used in urban environments may not be transferable to rural ones, further emphasizing a problem-solving approach. As Clary (2018) and Koper *et al.* (2021) have discovered, prevention strategies for rural HSI and fatal crashes, for example, may need to start in places that are *not* the crash location but an origin locale, such as a town bar.

This study is partially limited by the sample size of crashes at street segments and intersections, especially within a single year. This also hinders the HSI and LSI analysis because HSI crashes are rare. Future studies on spatial autocorrelation between HSI and LSI would provide more insight into low- and high-severity crash locations for prevention strategies. Other crash concentration calculation methods (e.g. Lorenz curve, Gini coefficient or Poisson distribution) could also be calculated for traffic crash concentration and yield more insights. Additionally, the levels of spatial crash concentration variations may be larger or smaller based on the boundaries of jurisdictions (spatial units) because the geographic characteristics of jurisdictions impact crash concentration calculations. The four-year temporal analysis may also be a relatively short time to measure temporal variations of crashes, and COVID-19 changed driving routines (at least temporarily) in 2020 and 2021. More analysis of those years would be helpful. Ultimately, more information on the specific environmental and routine activities that contribute to crashes at the specific places identified would be helpful to public safety agencies targeting these locations.

However, even with these limitations, the findings not only support Weisburd's law, but, more practically, emphasize to communities and the public safety agencies that serve them that crashes can be predicted and prevented by taking a strategic, evidence-based and targeted hot spots approach that relies on existing research knowledge in both the transportation and policing arenas.

Notes

1. Some have questioned Weisburd's law, arguing that concentrations may result from how they are calculated (see, e.g. Hipp and Kim, 2017; Oliveira *et al.*, 2017). Park and Lum (2021) also pondered whether the bandwidth of crime concentrations could be characterized as "narrow" given the variations that they discovered across multiple jurisdictions (although those variations still indicated high levels of spatial concentration of crime). But generally, there has been broad agreement that large proportions of crimes and disorders appear to be concentrated in a much smaller number of streets or small places.
2. See https://www.cdc.gov/injury/features/global-road-safety/index.html.
3. See https://www.gao.gov/blog/during-covid-19-road-fatalities-increased-and-transit-ridership-dipped.
4. The selection of Utah as the study location is purposeful, as the first author is a research partner with public safety agencies in this state.
5. See https://udot.utah.gov/connect/2023/01/05/udot-and-dps-release-2022-traffic-fatality-numbers/.
6. Utah crash reports encompass incidents involving injuries, fatalities or property damage exceeding $2,500 (see https://highwaysafety.utah.gov/crash-data/)
7. The total number of crashes (252,485) slightly differs from the total number of crashes at street segments and intersections listed in Appendix 1 (252,683) due to including crash counts that overlap on street segments connecting to other counties, such as interstate highways.
8. See https://support.esri.com/en-us/gis-dictionary/arc.
9. The authors used ArcGIS Pro 2.5 using the Utah Coordinate System of 1983 Central Zone.
10. See https://gis.utah.gov/data/transportation/roads-system/. If a crash coordinate did not fall on a street segment or location on this roads map, it was geocoded to the closest segment or intersection as determined by ArcGIS.
11. The authors could have just as well used average street segment length, given that Park (2019) has found a strong negative correlation between a jurisdiction's population density and average street segment length. This strong negative correlation also exists in Utah's counties ($r = -0.58, p < 0.001$).
12. Piute, Daggett and Wayne counties are excluded from Figure 3(b) due to the small number of crashes at intersections in those counties.

References

Alarifi, S.A., Abdel-Aty, M. and Lee, J. (2018), "A Bayesian multivariate hierarchical spatial joint model for predicting crash counts by crash type at intersections and segments along corridors", *Accident Analysis and Prevention*, Vol. 119, pp. 263-273.

Alkhadour, W., Zraqou, J., Al-Helali, A. and Al-Ghananeem, S.J.T. (2021), "Traffic accidents detection using geographic information systems (GIS)", *International Journal of Advanced Computer Science and Applications*, Vol. 12 No. 4, pp. 484-494.

Andresen, M.A., Curman, A.S. and Linning, S.J. (2017), "The trajectories of crime at places: understanding the patterns of disaggregated crime types", *Journal of Quantitative Criminology*, Vol. 33, pp. 427-449.

Barnum, T.C. and Nagin, D.S. (2021), "Ambiguity and legal compliance", *Criminology and Public Policy*, Vol. 20 No. 4, pp. 621-643.

Bassani, M., Rossetti, L. and Catani, L. (2020), "Spatial analysis of road crashes involving vulnerable road users in support of road safety management strategies", *Transportation Research Procedia*, Vol. 45, pp. 394-401.

Baumgartner, F.R., Epp, D.A. and Shoub, K. (2018), *Suspect Citizens: What 20 Million Traffic Stops Tell Us about Policing and Race*, Cambridge University Press, Cambridge.

Bioulac, S., Micoulaud-Franchi, J.-A., Arnaud, M., Sagaspe, P., Moore, N., Salvo, F. and Philip, P. (2017), "Risk of motor vehicle accidents related to sleepiness at the wheel: a systematic review and meta-analysis", *Sleep*, Vol. 40 No. 10, p. zsx134.

Braga, A.A., Turchan, B.S., Papachristos, A.V. and Hureau, D.M. (2019), "Hot spots policing and crime reduction: an update of an ongoing systematic review and meta-analysis", *Journal of Experimental Criminology*, Vol. 15, pp. 289-311.

Brantingham, P.L. and Brantingham, P.J. (1993), "Nodes, paths and edges: considerations on the complexity of crime and the physical environment", *Journal of Environmental Psychology*, Vol. 13 No. 1, pp. 3-28.

Bree, J. (2022), "Utah leaders announce more safety measures following a wave of deadly accidents", *Fox 13 Salt Lake City News*, available at: https://www.fox13now.com/news/local-news/following-multiple-deaths-utah-officials-discuss-ways-to-prevent-traffic-crashes

Brown, R.A. and Frank, J. (2005), "Police-citizen encounters and field citations: do encounter characteristics influence ticketing?", *Policing: An International Journal of Police Strategies and Management*, Vol. 28 No. 3, pp. 435-454.

Bunn, F., Collier, T., Frost, C., Ker, K., Roberts, I. and Wentz, R. (2003), "Traffic calming for the prevention of road traffic injuries: systematic review and meta-analysis", *Injury Prevention*, Vol. 9, pp. 200-204.

Burch, J. and Geraci, M. (2009), "Data-driven approaches to crime and traffic safety", *The Police Chief*, Vol. 76 No. 8, pp. 18-23.

Cai, Q., Abdel-Aty, M., Lee, J., Wang, L. and Wang, X. (2018), "Developing a grouped random parameters multivariate spatial model to explore zonal effects for segment and intersection crash modeling", *Analytic Methods in Accident Research*, Vol. 19, pp. 1-15.

Caird, J.K., Johnston, K.A., Willness, C.R., Asbrudge, M. and Steel, P. (2014), "A meta-analysis of the effects of texting on driving", *Accident Analysis and Prevention*, Vol. 71, pp. 311-318.

Carter, J.G. and Piza, E.L. (2018), "Spatiotemporal convergence of crime and vehicle crash hotspots: additional consideration for policing places", *Crime and Delinquency*, Vol. 64 No. 14, pp. 1795-1819.

Castro, M., Paleti, R. and Bhat, C.R. (2012), "A latent variable representation of count data models to accommodate spatial and temporal dependence: application to predicting crash frequency at intersections", *Transportation Research Part B: Methodological*, Vol. 46 No. 1, pp. 253-272.

Clary, K. (2018), "Utilizing data and science to reduce serious injury and fatality crashes on rural roadways", *Translational Criminology*, Vol. 15, pp. 12-13.

Cournoyer, C. (2011), "Data-driven policing", *Governing*, available at: www.governing.com/topics/public-justicesafety/Data-driven-Policing.html

Curman, A.S., Andresen, M.A. and Brantingham, P.J. (2015), "Crime and place: a longitudinal examination of street segment patterns in Vancouver, BC", *Journal of Quantitative Criminology*, Vol. 31, pp. 127-147.

de Winter, J.C.F. and Dodou, D. (2010), "The Driver Behaviour Questionnaire as a predictor of accidents: a meta-analysis", *Journal of Safety Research*, Vol. 41 No. 6, pp. 463-470.

Dezman, Z., de Andrade, L., Vissoci, J.R., El-Gabri, D., Johnson, A., Hirshon, J.M. and Staton, C.A. (2016), "Hotspots and causes of motor vehicle crashes in Baltimore, Maryland: a geospatial analysis of five years of police crash and census data", *Injury*, Vol. 47 No. 11, pp. 2450-2458.

Eck, J.E., Clarke, R.V. and Guerette, R.T. (2007), "Risky facilities: crime concentration in homogeneous sets of establishments and facilities", *Crime Prevention Studies*, Vol. 21, pp. 225-264.

Elvik, R. (1995), "Meta-analysis of evaluations of public lighting as accident countermeasure", *Transportation Research Record*, Vol. 1485 No. 1, pp. 12-24.

Elvik, R. (2001), "Area-wide urban traffic calming schemes: a meta-analysis of safety effects", *Accident Analysis and Prevention*, Vol. 33 No. 3, pp. 327-336.

Elvik, R. (2013), "Risk of road accident associated with the use of drugs: a systematic review and meta-analysis of evidence from epidemiological studies", *Accident Analysis and Prevention*, Vol. 60, pp. 254-267.

Engel, R.S. and Calnon, J.M. (2004), "Examining the influence of drivers' characteristics during traffic stops with police: results from a national survey", *Justice Quarterly*, Vol. 21 No. 1, pp. 49-90.

Fagan, J. and Davies, G. (2000), "Street stops and broken windows: terry, race, and disorder in New York City", *Fordham Urban Law Journal*, Vol. 28 No. 2, pp. 457-504.

Farrell, A. and McDevitt, J. (2006), *Rhode Island Traffic Stop Statistics Data Collection Study 2004-2005: Final Report*, Northeastern University Institute on Race and Justice, Boston, MA.

Felson, M.K. and Boba Santos, R. (2009), *Crime and Everyday Life*, 4th ed., Sage Publications, Thousand Oaks, CA.

Fisher, D.L., Breck, A., Gillham, O. and Flynn, D. (2021a), *Effectiveness of Dynamic Speed Feedback Signs, Volume I: Literature Review and Meta-Analysis*, Report No. DOT HS 813 170-A, National Highway Traffic Safety Administration, Washington, DC.

Fisher, D.L., Breck, A., Gillham, O. and Flynn, D. (2021b), *Effectiveness of Dynamic Speed Feedback Signs, Volume II: Technical Appendices and Annotated Bibliography*, Report No. DOT HS 813 170-B, National Highway Traffic Safety Administration, Washington, DC.

Giacopassi, D. and Forde, D.R. (2000), "Broken windows, crumpled fenders, and crime", *Journal of Criminal Justice*, Vol. 28 No. 5, pp. 397-405.

Gill, C., Wooditch, A. and Weisburd, D. (2017), "Testing the 'law of crime concentration at place' in a suburban setting: implications for research and practice", *Journal of Quantitative Criminology*, Vol. 33, pp. 519-545.

Groff, E.R., Weisburd, D. and Yang, S.M. (2010), "Is it important to examine crime trends at a local 'micro' level?: a longitudinal analysis of street to street variability in crime trajectories", *Journal of Quantitative Criminology*, Vol. 26, pp. 7-32.

Hasson, P. (1999), "Rural road safety: a global challenge", *Public Roads*, Vol. 63 No. 2, pp. 16-25.

Hibdon, J. (2013), *Crime Hot Spots in Suburbia: A Case Study. Presentation*, American Society of Criminology, Atlanta, GA.

Hipp, J.R. and Kim, Y.A. (2017), "Measuring crime concentration across cities of varying sizes: complications based on the spatial and temporal scale employed", *Journal of Quantitative Criminology*, Vol. 33, pp. 595-632.

Høye, A. (2014), "Speed cameras, section control, and kangaroo jumps–a meta-analysis", *Accident Analysis and Prevention*, Vol. 73, pp. 200-208.

Høye, A.K. and Hesjevoll, I.S. (2020), "Traffic volume and crashes and how crash and road characteristics affect their relationship – a meta-analysis", *Accident Analysis and Prevention*, Vol. 145, 105668.

Intini, P., Colonna, P. and Ryeng, E.O. (2019), "Route familiarity in road safety: a literature review and an identification proposal", *Transportation Research Part F: Traffic Psychology and Behavior*, Vol. 62, pp. 651-671.

Jaitman, L. and Ajzenman, N. (2016), Crime concentration and hot spot dynamics in Latin America, (No. IDB-WP-699). IDB Working Paper Series.

Johnson, S.D. and Bowers, K.J. (2004), "The burglary as clue to the future: the beginnings of prospective hot-spotting", *European Journal of Criminology*, Vol. 1 No. 2, pp. 237-255.

Koper, C.S., Lum, C., Wu, X., Goodier, M. and Clary, K. (2021), *The Iowa State Patrol Fatality Reduction Enforcement Report (FREE) Summary Evaluation Report*, Center for Evidence-Based Crime Policy, George Mason University, Fairfax, VA.

Kuo, P.F., Lord, D. and Walden, T.D. (2013), "Using geographical information systems to organize police patrol routes effectively by grouping hotspots of crash and crime data", *Journal of Transport Geography*, Vol. 30, pp. 138-148.

Li, G., Lai, W., Sui, X., Li, X., Qu, X., Zhang, T. and Li, Y. (2020), "Influence of traffic congestion on driver behavior in post-congestion driving", *Accident Analysis and Prevention*, Vol. 141, 105508.

Lum, C. and Koper, C.S. (2017), *Evidence-based Policing: Translating Research into Practice*, Oxford University Press, Oxford.

Lum, C., Koper, C.S., Wu, X., Johnson, W.D. and Stoltz, M. (2020), "Examining the empirical realities of proactive policing through systematic observations and computer-aided dispatch data", *Police Quarterly*, Vol. 23 No. 3, pp. 283-310.

Lum, C., Koper, C.S. and Wu, X. (2022), "Can we really defund the police? A nine-agency study of police response to calls for service", *Police Quarterly*, Vol. 25 No. 3, pp. 255-280.

Lundman, R.J. and Kaufman, R.L. (2003), "Driving while black: effects of race, ethnicity, and gender on citizen self-reports of traffic stops and police actions", *Criminology*, Vol. 41 No. 1, pp. 195-220.

Madensen, T.D. and Eck, J.E. (2008), "Violence in bars: exploring the impact of place manager decision-making", *Crime Prevention and Community Safety*, Vol. 10, pp. 111-125.

Michalowski, R.J. (1975), "Violence in the road: the crime of vehicular homicide", *Journal of Research in Crime and Delinquency*, Vol. 12 No. 1, pp. 30-43.

National Academies of Sciences, Engineering, and Medicine (2018), in Weisburd, D. and Majmundar, M. (Eds), *Proactive Policing: Effects on Crime and Communities*, The National Academies Press, Washington, DC.

National Center for Statistics and Analysis (NCSA) (2022), *Rural/urban Comparison of Traffic Fatalities: 2020 Data*, Traffic Safety Facts. Report No. DOT HS 813 336, National Highway Traffic Safety Administration, Washington, DC.

National Highway Traffic Safety Administration (NHTSA) (2013), *Data Driven Approaches to Crime and Traffic Safety (DDACTS): An Historical Overview*, Report No. DOT HS 809 689, National Highway Traffic Safety Administration, Washington, DC.

National Highway Traffic Safety Administration (NHTSA) (2014), *Data-Driven Approaches to Crime and Traffic Safety, Operational Guidelines*, National Highway Traffic Safety Administration, Washington, DC.

National Highway Traffic Safety Administration (NHTSA) (2022), *Speeding: Traffic Safety Facts*, Report No. DOT HS 813 320, National Highway Traffic Safety Administration, Washington, DC.

National Research Council (2004), in Skogan, W. and Frydl, K. (Eds), *The Growth of Incarceration in the United States: Exploring Causes and Consequences*, The National Academies Press, Washington, DC.

Oliveira, M., Bastos-Filho, C. and Menezes, R. (2017), "The scaling of crime concentration in cities", *PloS One*, Vol. 12 No. 8, e0183110.

Park, S. (2019), Examining the "law of crime concentrations" across multiple jurisdictions, Doctoral dissertation, George Mason University.

Park, S. (2022), "How one Utah city is trying to curb trend of fatal crashes. KSLTV.com (an NBC affiliate)", available at: https://ksltv.com/496508/how-one-utah-city-is-trying-to-curb-trend-of-fatal-crashes/

Park, S. and Lum, C. (2021), "Examining the generalizability of Weisburd's law of crime concentration", available at: SSRN 4382299.

Phillips, R.O., Ulleberg, P. and Vaa, T. (2011), "Meta-analysis of the effect of road safety campaigns on accidents", *Accident Analysis and Prevention*, Vol. 43 No. 3, pp. 1204-1218.

Pierson, E., Simoiu, C., Overgoor, J., Corbett-Davies, S., Jenson, D., Shoemaker, A., Ramachandran, V., Barghouty, P., Phillips, C., Shroff, R. and Goel, S. (2020), "A large-scale analysis of racial disparities in police stops across the United States", *Nature Human Behaviour*, Vol. 4 No. 7, pp. 736-745.

Plug, C., Xia, J.C. and Caulfield, C. (2011), "Spatial and temporal visualisation techniques for crash analysis", *Accident Analysis and Prevention*, Vol. 43 No. 6, pp. 1937-1946.

Porchia, B.R., Baldasseroni, A., Dellisanti, C., Lorini, C. and Bonaccorsi, G. (2014), "Effectiveness of two interventions in preventing traffic accidents: a systematic review", *Annali di Igiene: Medicina Preventiva e di Comunita*, Vol. 26 No. 1, pp. 63-75.

Rahman, M.T., Jamal, A. and Al-Ahmadi, H.M. (2020), "Examining hotspots of traffic collisions and their spatial relationships with land use: a GIS-based geographically weighted regression approach for Dammam, Saudi Arabia", *ISPRS International Journal of Geo-Information*, Vol. 9 No. 9, p. 540.

Saha, S., Schramm, P., Nolan, A. and Hess, J. (2016), "Adverse weather conditions and fatal motor vehicle crashes in the United States, 1994-2012", *Environmental Health*, Vol. 15, p. 104.

Shaaban, K. and Ibrahim, M. (2021), "Analysis and identification of contributing factors of traffic crashes in New York City", *Transportation Research Procedia*, Vol. 55, pp. 1696-1703.

Sherman, L.W., Gartin, P.R. and Buerger, M.E. (1989), "Hot spots of predatory crime: routine activities and the criminology of place", *Criminology*, Vol. 27 No. 1, pp. 27-56.

Simpson, R., McCutcheon, M. and Lal, D. (2020), "Reducing speeding via inanimate police presence: an evaluation of a police-directed field study regarding motorist behavior", *Criminology and Public Policy*, Vol. 19 No. 3, pp. 997-1018.

Smith, M.R. and Petrocelli, M. (2001), "Racial profiling? A multivariate analysis of police traffic stop data", *Police Quarterly*, Vol. 4 No. 1, pp. 4-27.

Smith, W.R., Frazee, S.G. and Davison, E.L. (2000), "Furthering the integration of routine activity and social disorganization theories: small units of analysis and the study of street robbery as a diffusion process", *Criminology*, Vol. 38 No. 2, pp. 489-524.

Stanojević, P., Sullman, M.J., Jovanović, D. and Stanojević, D. (2018), "The impact of police presence on angry and aggressive driving", *Accident Analysis and Prevention*, Vol. 110, pp. 93-100.

Stuster, J. (2001), Report No. DOT HS 809 278, National Highway Traffic Safety Administration, Washington, DC, Albuquerque police department: Safe streets program.

Su, Z., Woodman, R., Smyth, J. and Elliott, M. (2023), "The relationship between aggressive driving and driver performance: a systematic review with meta-analysis", *Accident Analysis and Prevention*, Vol. 183, 106972.

Wang, K., Ivan, J.N., Ravishanker, N. and Jackson, E. (2017), “Multivariate Poisson lognormal modeling of crashes by type and severity on rural two lane highways”, *Accident Analysis and Prevention*, Vol. 99 No. Pt A, pp. 6-19.

Weisburd, D. (2015), “The law of crime concentration and the criminology of place”, *Criminology*, Vol. 53 No. 2, pp. 133-157.

Weisburd, D. and Amram, S. (2014), “The law of concentrations of crime at place: the case of Tel Aviv-Jaffa”, *Police Practice and Research*, Vol. 15 No. 2, pp. 101-114.

Weisburd, D. and Eck, J.E. (2018), *Unraveling the Crime-Place Connection: New Directions in Theory and Policy*, Routledge, New York, NY.

Weisburd, D. and Green, L. (1995), “Policing drug hot spots: the Jersey City drug market analysis experiment”, *Justice Quarterly*, Vol. 12 No. 4, pp. 711-735.

Weisburd, D., Bushway, S., Lum, C. and Yang, S.M. (2004), “Trajectories of crime at places: a longitudinal study of street segments in the city of Seattle”, *Criminology*, Vol. 42 No. 2, pp. 283-322.

Weisburd, D., Morris, N.A. and Groff, E.R. (2009), “Hot spots of juvenile crime: a longitudinal study of arrest incidents at street segments in Seattle, Washington”, *Journal of Quantitative Criminology*, Vol. 25, pp. 443-467.

Weisburd, D., Groff, E.R. and Yang, S.M. (2012), *The Criminology of Place: Street Segments and Our Understanding of the Crime Problem*, Oxford University Press, Oxford.

Weisburd, D., Eck, J.E., Braga, A.A., Telep, C.W., Cave, B., Bowers, K., Bruinsma, G., Gill, C., Groff, E., Hibdon, J., Hinkle, J., Johnson, S.D., Lawton, B., Lum, C., Ratcliffe, J.H., Rengert, G., Taniguchi, T. and Yang, S.-M. (2016), *Place Matters: Criminology for the Twenty-First Century*, Cambridge University Press, New York, NY.

Wheeler, A.P., Worden, R.E. and McLean, S.J. (2016), “Replicating group-based trajectory models of crime at micro-places in Albany, NY”, *Journal of Quantitative Criminology*, Vol. 32, pp. 589-612.

Wikström, P.O.H., Oberwittler, D., Treiber, K. and Hardie, B. (2012), *Breaking Rules: The Social and Situational Dynamics of Young People’s Urban Crime*, Oxford University Press, Oxford.

Williams, C. (2023a), 6 Utah projects to receive $3.2M from ‘historic’ $800M grant to curb US traffic fatalities. KSL.com news, available at: https://www.ksl.com/article/50570879/6-utah-projects-to-receive-32m-from-historic-800m-grant-to-curb-us-traffic-fatalities

Williams, C. (2023b), “Utah Communities Begin Work on ‘historic Effort’ to Improve Road Safety, Curb Traffic Deaths. KSL.Com News”, available at: https://www.ksl.com/article/50609047/utah-communities-begin-work-on-historic-effort-to-improve-road-safety-curb-traffic-deaths

Wu, X. and Lum, C. (2019), “The practice of proactive traffic stops”, *Policing: An International Journal*, Vol. 43 No. 2, pp. 229-246.

Wu, X., Lum, C. and Koper, C.S. (2021), “Do everyday proactive policing activities reduce vehicle crashes? Examining a commonly held law enforcement belief using a novel method”, *Journal of Criminal Justice*, Vol. 76, 101846.

Zhang, W., Liu, T. and Yi, J. (2022), “Exploring the spatiotemporal characteristics and causes of rear-end collisions on urban roadways”, *Sustainability*, Vol. 14 No. 18, 11761.

Corresponding author
Sangjun Park can be contacted at: sangjunpark1@suu.edu

Appendix 1

Table A1.
Characteristics of all 29 counties in Utah

County	Area (sq mi)	Population	PD	All crash	Crash at street segments	Number of street segments	Crash at street intersections	Number of street intersections	Median length of street segments (feet)
SALT LAKE	808	1,165,517	1,443	109,904	63,956	49,800	45,948	29,523	339
DAVIS	634	359,232	567	23,443	14,577	16,389	8,866	9,760	374
WEBER	659	262,658	398	17,381	9,284	13,014	8,097	7,408	431
UTAH	2,141	651,059	304	40,830	23,692	30,958	17,138	18,377	396
CACHE	1,173	130,004	111	8,750	4,788	8,760	3,962	5,013	669
WASHINGTON	2,430	184,913	76	11,331	6,368	16,970	4,963	10,210	479
WASATCH	1,209	35,300	29	3,098	2,302	5,216	796	3,130	826
SUMMIT	1,882	42,499	23	4,679	3,515	7,498	1,164	4,802	832
MORGAN	611	12,462	20	844	799	2,979	45	1,714	1,274
SANPETE	1,603	31,393	20	1,522	1,203	7,712	319	4,784	1,094
IRON	3,302	56,814	17	3,983	2,738	12,011	1,245	7,720	1,294
CARBON	1,485	20,760	14	1,721	1,307	6,073	414	3,553	1,050
SEVIER	1,918	21,780	11	1,540	1,282	8,006	258	6,564	840
TOOELE	7,287	74,512	10	4,716	3,204	12,909	1,512	8,295	966
BOX ELDER	6,729	57,007	9	5,100	4,172	9,794	928	6,293	1,338
UINTAH	4,499	35,970	8	1,988	1,405	13,006	583	8,354	1,343
DUCHESNE	3,256	19,894	6	1,435	1,127	7,325	308	4,970	1,414
JUAB	3,406	12,122	4	1,444	1,345	8,071	99	4,879	1,701
GRAND	3,694	9,796	3	1,217	972	25,029	245	14,246	750
BEAVER	2,592	6,761	3	889	833	8,125	56	5,931	1,898
EMERY	4,462	10,147	2	1,112	1,027	7,486	85	4,945	1,335
RICH	1,086	2,452	2	353	326	3,267	27	2,577	1,600
MILLARD	6,828	13,327	2	1,681	1,529	14,423	152	8,686	1,888
SAN JUAN	7,933	15,278	2	1,238	1,136	16,087	102	9,476	1,362
KANE	4,108	7,914	2	1,023	938	6,940	85	4,151	1,432
PIUTE	766	1,473	2	144	137	3,694	7	2,408	1,088
DAGGETT	723	1,026	1	128	118	1,653	10	967	1,315
WAYNE	2,466	2,759	1	278	260	3,830	18	2,813	1,161
GARFIELD	5,208	5,050	1	911	818	8,287	93	5,023	1,449
UTAH	*84,899*	*3,249,879*		*252,683*	*155,158*	*335,312**	*97,525*	*206,572*	

Note(s): Abbreviation: PD = Population Density (persons per square mile). A Pearson's correlations analysis was performed to examine the associations among several variables. The results indicated strong positive correlations between population density (PD) and the number of street segments ($r = 0.80$, $p < 0.0001$), as well as between PD and the number of street intersections ($r = 0.80$, $p < 0.0001$). Additionally, there was a moderate negative correlation between PD and the median length of street segments ($r = -0.58$, $p < 0.001$). Finally, a very strong positive correlation was observed between the number of street segments and the number of street intersections ($r = 0.99$, $p < 0.0001$)
Source(s): Area and Population (National Center for Health Statistics https://ibis.health.utah.gov, 2022). Table by authors

Appendix 2

County	Street 25%	Street 50%	Street 75%	Street 100%	Intersection 25%	Intersection 50%	Intersection 75%	Intersection 100%
SALT LAKE	0.19	0.94	3.90	22.91	0.36	1.22	3.98	23.73
DAVIS	0.13	0.52	2.34	15.78	0.29	1.07	3.38	17.09
WEBER	0.25	1.15	4.03	16.86	0.46	1.42	4.02	18.95
UTAH	0.10	0.58	2.59	15.24	0.36	1.24	3.81	17.29
CACHE	0.21	1.07	3.79	14.52	0.36	1.20	3.53	15.86
WASHINGTON	0.21	0.78	2.56	9.80	0.21	0.71	2.06	9.75
WASATCH	0.17	0.65	2.11	9.70	0.19	0.70	2.36	7.70
SUMMIT	0.24	0.75	2.20	9.79	0.12	0.44	1.58	6.33
MORGAN	0.13	0.34	0.84	4.26	0.18	0.41	0.99	1.63
SANPETE	0.19	0.70	2.15	5.77	0.23	0.90	2.40	4.06
IRON	0.12	0.46	1.48	5.67	0.13	0.45	1.31	4.44
CARBON	0.25	0.97	2.93	7.94	0.17	0.62	1.63	4.48
SEVIER	0.07	0.27	1.00	4.06	0.12	0.46	1.26	2.24
TOOELE	0.12	0.46	1.87	7.13	0.07	0.23	0.88	4.05
BOX ELDER	0.13	0.48	1.77	8.81	0.19	0.79	2.27	5.96
UINTAH	0.11	0.49	1.53	4.04	0.10	0.30	0.87	2.43
DUCHESNE	0.25	0.86	2.35	6.05	0.10	0.46	1.49	3.04
JUAB	0.05	0.14	0.55	3.18	0.16	0.55	1.07	1.56
GRAND	0.05	0.18	0.55	1.45	0.04	0.10	0.29	0.72
BEAVER	0.02	0.06	0.25	1.92	0.08	0.24	0.47	0.71
EMERY	0.08	0.33	0.95	3.62	0.18	0.61	1.03	1.48
RICH	0.06	0.21	0.52	2.20	0.12	0.35	0.62	0.85
MILLARD	0.05	0.16	0.55	2.49	0.15	0.44	0.87	1.31
SAN JUAN	0.06	0.24	0.81	2.41	0.05	0.17	0.44	0.71
KANE	0.13	0.36	0.88	2.91	0.05	0.19	0.55	1.06
PIUTE	0.11	0.22	0.54	1.33	0.04	0.12	0.21	0.25
DAGGETT	0.36	0.91	1.75	3.51	0.31	0.52	0.83	1.03
WAYNE	0.13	0.52	1.51	3.21	0.11	0.25	0.43	0.57
GARFIELD	0.10	0.40	1.11	3.04	0.06	0.24	0.62	1.08
Average	0.14	0.52	1.70	6.88	0.17	0.56	1.56	5.53

Table A2. All crash concentrations calculations for 25%, 50%, 75% and 100% of crashes at street segments and intersections for all 29 counties in Utah

Appendix 3

Table A3.
Crash concentrations calculations for 25%, 50%, 75% and 100% of various categories of crashes at street segments and intersections for all 29 counties in Utah

County	Low-severity injury (LSI)								High-severity injury (HSI)							
	Street				Intersection				Street				Intersection			
	25%	50%	75%	100%	25%	50%	75%	100%	25%	50%	75%	100%	25%	50%	75%	100%
SALT LAKE	0.19	0.93	3.89	22.74	0.36	1.21	3.97	23.51	0.14	0.48	0.95	1.42	0.20	0.61	1.43	2.28
DAVIS	0.13	0.51	2.31	15.60	0.29	1.07	3.38	16.90	0.09	0.24	0.57	0.90	0.16	0.46	0.89	1.32
WEBER	0.25	1.15	4.01	16.67	0.46	1.42	4.04	18.82	0.18	0.58	0.98	1.38	0.26	0.67	1.31	1.96
UTAH	0.10	0.57	2.55	14.98	0.36	1.24	3.82	17.17	0.07	0.25	0.65	1.05	0.14	0.47	0.90	1.33
CACHE	0.19	1.07	3.77	14.33	0.36	1.18	3.49	15.62	0.10	0.30	0.57	0.83	0.22	0.58	0.94	1.30
WASHINGTON	0.21	0.77	2.52	9.56	0.21	0.71	2.04	9.59	0.10	0.33	0.63	0.93	0.10	0.33	0.57	0.79
WASATCH	0.17	0.65	2.09	9.34	0.19	0.70	2.36	7.48	0.13	0.38	0.94	1.55	0.13	0.42	0.70	0.99
SUMMIT	0.24	0.75	2.20	9.60	0.12	0.44	1.62	6.29	0.12	0.29	0.72	1.13	0.04	0.10	0.29	0.46
MORGAN	0.13	0.34	0.81	4.06	0.18	0.41	0.93	1.52	0.10	0.27	0.47	0.67				
SANPETE	0.19	0.69	2.10	5.61	0.23	0.90	2.32	3.93	0.12	0.25	0.38	0.51	0.06	0.10	0.17	0.21
IRON	0.12	0.47	1.49	5.55	0.13	0.45	1.30	4.39	0.07	0.18	0.41	0.63	0.05	0.14	0.25	0.34
CARBON	0.25	0.94	2.85	7.74	0.20	0.62	1.63	4.42	0.15	0.28	0.43	0.56	0.06	0.08	0.11	0.14
SEVIER	0.07	0.27	1.00	3.93	0.12	0.46	1.25	2.19	0.05	0.14	0.32	0.52	0.03	0.06	0.09	0.11
TOOELE	0.12	0.47	1.85	6.89	0.07	0.23	0.86	3.95	0.06	0.20	0.51	0.81	0.04	0.14	0.25	0.36
BOX ELDER	0.13	0.48	1.74	8.56	0.19	0.81	2.34	5.94	0.11	0.32	0.66	1.01	0.06	0.14	0.22	0.29
UINTAH	0.11	0.49	1.51	3.99	0.10	0.30	0.85	2.39	0.02	0.08	0.16	0.24	0.04	0.06	0.10	0.12
DUCHESNE	0.25	0.86	2.31	5.98	0.10	0.44	1.49	3.00	0.04	0.14	0.26	0.37	0.04	0.06	0.08	0.10
JUAB	0.05	0.14	0.52	2.97	0.16	0.53	1.02	1.52	0.05	0.15	0.30	0.48				
GRAND	0.05	0.17	0.50	1.34	0.04	0.09	0.29	0.71	0.03	0.10	0.17	0.24	0.01	0.02	0.04	0.04
BEAVER	0.02	0.06	0.25	1.85	0.08	0.24	0.46	0.67	0.02	0.05	0.14	0.25				
EMERY	0.08	0.33	0.96	3.50	0.18	0.59	1.01	1.42	0.03	0.11	0.27	0.49				
RICH	0.06	0.18	0.46	2.02	0.12	0.27	0.47	0.66	0.06	0.15	0.31	0.43	0.08	0.12	0.19	0.23
MILLARD	0.05	0.16	0.53	2.39	0.15	0.44	0.85	1.27	0.03	0.09	0.21	0.33	0.02	0.05	0.07	0.08
SAN JUAN	0.06	0.22	0.75	2.25	0.05	0.17	0.42	0.68	0.03	0.11	0.19	0.27	0.02	0.03	0.04	0.05
KANE	0.13	0.36	0.88	2.84	0.05	0.19	0.53	0.99	0.03	0.09	0.17	0.26	0.02	0.07	0.12	0.14
PIUTE	0.11	0.19	0.51	1.30	0.04	0.08	0.17	0.21	0.05	0.11	0.16	0.22				
DAGGETT	0.30	0.85	1.63	3.21	0.31	0.52	0.83	1.03	0.12	0.18	0.30	0.36				
WAYNE	0.13	0.50	1.46	3.03	0.11	0.25	0.39	0.53	0.08	0.21	0.34	0.44				
GARFIELD	0.10	0.36	1.03	2.79	0.06	0.20	0.58	1.00	0.08	0.28	0.47	0.66	0.06	0.10	0.14	0.18
Average	0.14	0.52	1.67	6.71	0.17	0.56	1.54	5.44	0.08	0.22	0.44	0.65	0.08	0.19	0.36	0.58

Note(s): The HSI table has missing values because there were fewer than four crashes with HSI in each county, and only a few street intersections generated up to three HSI crashes. As a result, some crash concentration calculations have the same percentage of locations and have not been included here
Source(s): Table by authors