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Random Acts of Violence? Examining Probabilistic Independence of the Temporal Distribution of Mass Killing Events in the United States

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Recent mass killings such as those in Newtown, CT and Aurora, CO, have brought new attention to mass killings in the United States. This article examines 323 mass killings taking place between January 1, 2006, and October 4, 2016 to assess how they are distributed over time. In particular, we find that they appear to be uniformly distributed over time, which suggests that their rate has remained stable over the past decade. Moreover, analysis of subsets of these mass killings sharing a common trait (e.g., family killings, public killings) suggests that they exhibit a memoryless property, suggesting that mass killing events within each category are random in the sense that the occurrence of one mass killing event does not signal whether another mass killing event is imminent. However, the same memoryless property is not found when combining all mass killings into a single analysis, consistent with earlier research that found evidence of a contagion effect among mass killing events. Due to the temporal randomness of public mass killings and the wide geographic area over which they can occur, these results imply that these events may be best addressed by systemic infrastructure-based interventions that deter such events, incorporate resiliency into the response system, or impede such events until law enforcement can respond when they do occur.

Keywords: mass killings, Poisson process, probability, statistics, stochastic process, violence

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1. Introduction

Recent mass killings such as those in Aurora, CO, on July 20, 2012, and Newtown, CT, on December 14, 2012, have brought new attention to mass killings in the United States. Active shooter events were recently found to have increased between 2000 and 2012, where an active shooter event involves an individual attempting to commit mass murder, with at least one target not related to the shooter (Blair et al. 2014). The Federal Bureau of Investigation (FBI) defines a mass killing as an event in which four or more victims are killed (Huff-Corzine et al. 2014; USA Today, 2016). Hence, an active shooter event and a mass killing are not equivalent; for example, a mass killing could include family killings in which all victims are related to the suspect or in which no firearms were involved, while an active shooter event could result in fewer than four victim deaths. Due to these distinctions, it is necessary to analyze mass killings separately from active shooter events to investigate whether recent increases in active shooter events also correspond to increases in mass killings in the United States. As policymakers seek strategies that discourage and prevent active shooter events and mass killings, being able to distinguish between trends in mass killings and those in active shooters allows more nuanced policies to be crafted.

While recent mass killings have generated considerable national attention in the United States, Duwe (2000, 2005) reports that mass killings that gain the most nationwide attention tend to over-represent mass killings such as those with large fatality counts, those committed with assault weapons, those whose victims are strangers to the perpetrator, or those taking place in public places, potentially leading the general public to an incorrect and limited view of the characteristics of mass killings. For example, this view is likely to underrepresent familicides,

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defined as the killing of multiple family members; a study of news reports from 1900-1999 found that only 18% of news stories on mass killings included family victims, though 44% of mass killings in the same period included family victims (Duwe 2000). Such familicides have been well-studied in the literature, with a number of studies examining their psychological characteristics and financial circumstances (e.g., Malmquist 1980, Liem and Koenraadt 2008, Liem et al. 2013, Liem and Reichelmann 2014). Moreover, USA Today data indicate that 53% of mass killings from January 2006 to October 2016 were classified as family killings; while this classification differs from familicide, in that the victims need not be direct family members of the perpetrator, it does signify some social or family relationship between the perpetrator and the victims, and hence, excludes victims that are exclusively strangers (USA Today 2016). Any policy aiming to address mass killings must reflect the prevalence of such family killings.

A study of mass killings in the twentieth century showed that the number of mass killings remained relatively low until the mid-1960s, other than a spike in the 1920s and 1930s (Duwe 2004); according to FBI data beginning in the mid-1970s, an average of approximately 26 mass killings occurred annually from 1976 to 1999 (Duwe 2000, 2004), while USA Today reports an average of 30 mass killings per year from 2006 to 2016 (USA Today 2016), representing a 13% increase in mass killings in the twenty-first century, though these differences could also be due to differences in data sources and classifications. Several studies have examined mass killings, in an attempt to discern the underlying psychological and behavioral characteristics of their perpetrators (e.g., Palermo 1997, Langman 2009, Declercq and Audenaert 2011, Scheff 2011).

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This paper aims to help policymakers place recent high-profile mass killings into appropriate context, in light of the increased attention paid to the role of media in portraying risk to the public and the potential underrepresentation of some types of mass killings (e.g., Kitzinger 1999, Duwe 2000, Duwe 2005). To accomplish this goal, this paper analyzes data on the 323 mass killings documented by USA Today to examine how they are distributed over time; these mass killings took place between January 1, 2006 and October 4, 2016 (USA Today 2016). Each mass killing is classified in several ways, including method (e.g., shooting, stabbing) and type (e.g., family killing, public killing). Using these classifications, this paper also analyzes several subsets of these mass killings to draw conclusions about how mass killings in each category occur over time. To conduct these analyses, each set of mass killings is viewed as a *stochastic process*, in which events (i.e., mass killings) occur at discrete points in time that are not predictable in advance. The analysis of crime events as a stochastic process has a long history in the field of operations research; Blumstein (2002) provides an overview of some applications.

A recent study of mass killings as a stochastic process found evidence of a contagion effect among mass killing events between 2006 and 2013 under the initial hypothesis of one mass killing triggering others to perpetrate similar events (Towers et al. 2015). This contagion approach applies an excitation period following each mass killing event, such that subsequent mass killings are more likely to occur during this excitation period, and finds this excitation period to be statistically significant. This contagion is modeled to be homogeneous, such that any mass killing event gives rise to such an excitation period. However, the ability of one event to trigger other events should intuitively be based on awareness of the triggering event; awareness of a public mass killing that receives national media attention is more likely than a family mass

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killing that does not receive this degree of coverage. Alternatively, a contagion effect could potentially be more influential on events of the same type or method (e.g., a contagion of family killings). Hence, analyzing the temporal distribution of a more homogeneous set of mass killing events, such as those exhibiting the same type or method, can provide additional insights regarding potential relationships between these events.

The two questions that this paper seeks to answer are (1) whether the rate of mass killings has increased between 2006 and 2016, and (2) whether mass killings are temporally random, such that the occurrence of one mass killing indicates that other mass killings are imminent. Answering the first question provides insight into whether an increasing trend like the one observed for active shooter events (Blair et al. 2014) is also observed for mass killing events, while analyzing single categories of mass killings allows policymakers to draw more finegrained conclusions about mass killing events and how to develop policies that could interrupt or deter them. For example, if public killings were becoming more frequent but family killings were becoming less frequent, then analyzing all mass killing events together could show a stable rate, even though this conclusion would not be true for these two categories of mass killings. From a policymaking perspective, being able to separate trends in different categories would permit the development of more nuanced policies that address these differing trends. Answering the second question can indicate whether the contagion effect observed among all mass killing events is also observed in more homogeneous sets of mass killings events of a single type or method, and can suggest whether additional resources should be deployed immediately following a mass killing in preparation for other mass killings, such as copycat phenomena. Taken together, answering the two proposed questions can help policymakers evaluate resource allocations and policy efforts.

This paper is organized as follows. Section 2 presents the data used in this paper, as well as the methods that are used to investigate the two questions posed above. Section 3 discusses the results of these analyses. Section 4 discusses the limitations of these results and directions of future research, while Section 5 presents concluding remarks, including policy implications.

2. Materials and Methods

In the aftermath of the Navy Yard shooting in Washington, DC, on September 16, 2013, USA Today published a list of thirty-two public shootings that had taken place in the United States between 2006 and 2013 (USA Today 2013). USA Today has since published additional data on an accompanying website, extending these data to included mass killings, rather than public shootings, and cataloging 323 separate incidents occurring between January 1, 2006 and October 4, 2016; this expanded data set represents a composite of data from FBI reports, local news reports, official records, and information from local law enforcement, with USA Today noting that FBI reports in isolation were found to be incomplete and sometimes inaccurate (USA Today 2016). Similar concerns about data completeness and reliability have already been discussed in the literature (Huff-Corzine et al. 2014), including the possible risk that media sources may lack exhaustive data. However, by combining FBI data with additional reporting, it is presumed that the USA Today data set represents a sufficiently exhaustive set of mass killing events over the covered time period. An incident is classified as a mass killing if it results in at least four victim fatalities (omitting deaths of any suspects) during a relatively short period of time (to distinguish from serial killings) (USA Today 2016).

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Each of the 323 incidents cataloged by USA Today is classified by its date, number of victim fatalities, location (state and place), method of killings (e.g., weapon used), and type of killing (e.g., family killing, public killing). In addition to analysis of the entire set of 323 mass killings, more fine-grained analysis of several individual categories is also conducted to allow conclusions to be drawn about each category of mass killings, with analysis restricted to categories containing at least thirty mass killings. Events solely categorized as "Other" or "Unknown" are omitted from category-specific analysis, as they do not reflect mass killing events sharing a known common trait. By these restrictions, analysis will be performed on mass killings classified by type as family killings (172 events), public killings (52 events), and burglary/robbery killings (34 events); the remaining types of mass killings contained in the USA Today data set are classified as either unknown (8 events) or other (57 events). Analysis will also be conducted for mass killings classified by method as shootings (244 events), stabbings (39 events), and arson, smoke inhalation, or burns (31 events); the remaining types are blunt force (21 events), carbon monoxide poisoning (1 event), drowning (2 events), strangulation (8 events), suffocation (2 events), and unknown/other (10 events). While each mass killing has a single category for its type, mass killings can be classified under multiple methods; for example, eight mass killings are classified as both shootings and stabbings, and are included in both of these subsets in the analysis conducted in this article.

Two sets of hypotheses are proposed to investigate the two questions posed at the end of Section 1, each involving comparisons between two probability distributions. First, the question of whether the rate of mass killings has increased between 2006 and 2016 is assessed using a *uniformity test*, where the temporal distribution of mass events over time is compared with a

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uniform distribution from January 1, 2006, to October 4, 2016. If mass killings occur more frequently over time, then these events should not be spread uniformly over time, and the distributions should exhibit significant differences. Second, the question of whether mass killings are random, such that the occurrence of one mass killing indicates that other mass killings are imminent, is assessed using an *interrarrival test* that compares the elapsed time between consecutive mass killing events with an exponential distribution. A stochastic process in which interarrival times have a homogeneous exponential distribution is called a *Poisson process*, and exhibits a well-known memoryless property in which the time until the next event will occur is independent of the amount of time since the last event occurred (Ross 2007). If such a property applies to a sequence of mass killings, it would suggest that these events occur randomly in the sense that the next mass killing event does not become more or less imminent as the most recent mass killing event recedes into the past. Hence, if mass killing events are random in this sense, then their interarrival times should not exhibit significant differences from the exponential distribution.

Both types of analyses of the USA Today data set conducted in this article examine the distribution of mass killing events over time, comparing observed mass killings with a hypothesized probability distributions using the Kolmogorov-Smirnov test (Feller 1948). This test compares the cumulative distribution functions of the observed and hypothesized distributions under the null hypothesis that the compared distributions are identical and an alternative hypothesis that the distributions differ. The test statistic, D, is equal to the maximum absolute discrepancy between the hypothesized and observed cumulative distribution functions. The null hypothesis is rejected at significance level α if D exceeds the critical value, D_{α} , which

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decreases as the sample size increases; for example, when $\alpha = 0.05$ the critical value is $D_{\alpha} = 0.24$ for n = 30 and $D_{\alpha} = 1.36n^{-1/2}$ for n > 35 (Massey 1951). In other words, as the sample size grows, the test permits less discrepancy between the hypothesized and actual observed distributions before rejecting the null hypothesis. The uniformity test compares the overall distribution of these events over between January 1, 2006 and October 4, 2016, to assess whether this distribution differs significantly from a uniform distribution over the same dates. The interarrival test considers the times between consecutive mass killings, comparing their distribution to an exponential distribution. The exponential distribution is characterized by a mean parameter, μ , which is estimated as the sample mean of observed interarrival times in each analyzed subset (i.e., the maximum likelihood estimator for μ); since this parameter is estimated from data, the critical values of the Kolmogorov-Smirnov test take smaller values in the interarrival test, and less discrepancy between the distributions is allowed before rejecting the null hypothesis (Lillefors 1969).

3. Results

Both the uniformity test and the interarrival test were applied to the entire set of 323 mass killings, as well as each of the six categories of mass killings discussed in the preceding section. These analyses were conducted by the authors using the Microsoft Excel and MatLab software packages. The results of these tests are depicted in Table 1, which reports test statistics for both tests, along with the *p*-value of each uniformity test and the estimated mean (in days) of each exponential distribution for each interarrival test. From these data, it is clear that shootings are the most common method of mass killing, comprising 76% (244/323) of all mass killings taking

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place between January 1, 2006 and October 4, 2016. Similarly, family killings are the most common type of mass killing, making up 53% (172/323) of mass killings.

Category	Number of Events	Uniformity Test		Interarrival Test	
		Test	<i>p</i> -value	Test	Mean
		Statistic		Statistic ¹	(days)
All	323 (100%)	0.0594	0.1966	0.0801***	12.13
Shootings	244 (76%)	0.0465	0.6488	0.0603*	16.06
Stabbings	39 (12%)	0.1152	0.6369	0.1253	100.41
Arson/Burns/Smoke	31 (9.6%)	0.1808	0.2331	0.1313	125.39
Family Killings	172 (53%)	0.0592	0.5616	0.0748**	22.77
Public Killings	52 (16%)	0.1238	0.3725	0.1382**	75.35
Robbery/Burglary	34 (10%)	0.2077	0.0918	0.1040	102.41

Table 1. Results of the Uniformity Test and Interarrival Te	st
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¹ *p*-values bounds: p < 0.01 (***), 0.05 (**), <math>0.10 (*), <math>p > 0.20 (unmarked) (Lillefors 1969)

The results of the uniformity test in Table 1 suggest that mass killings appear to have occurred at a stable rate over time from January 1, 2006, to October 4, 2016, as their temporal distribution does not differ significantly from the uniform distribution at the $\alpha = 0.05$ significance level. Moreover, this same result is observed for each of the six categories of mass killings analyzed in this study. These results imply that the rate of mass killings has remained stable over this decade, as have the rates of mass killings in each of the six categories.

When all mass killings are analyzed together, the results in Table 1 indicate that their interarrival distribution differs significantly from the exponential distribution at the $\alpha = 0.05$ significance level, suggesting that they do not bear the memoryless property. This significant result suggests some non-randomness that could potentially be attributed to a contagion effect suggested in prior

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literature (Towers et al. 2015) or some other source of influence of mass killings. However, this analysis considers events bearing a variety of types and methods. Due to the diversity of these events, analysis of a single category of mass killings with a single type of method may yield clearer insights into the temporal distribution of a more homogeneous set of mass killings. When each category is analyzed separately, their interarrival times are indistinguishable from the exponential distribution at the $\alpha = 0.05$ significance level, suggesting that mass killings in each of these six categories exhibit the memoryless property inherent to the exponential distribution.

As noted in Section 2, the results of the uniformity and interarrival tests have two distinct implications. The results of the uniformity test show that each subset of mass killings is distributed approximately uniformly over the period from January 1, 2006, to October 4, 2016. This result implies that each category of mass killings has occurred at a stable rate over this tenyear span. However, the uniformity test alone cannot show that mass killings are temporally random. For example, suppose that each mass killing took place exactly twelve days after the previous mass killing; while this hypothetical scenario would display a stable rate of mass killings, these mass killings could not be considered random, as the time of the next mass killing could be predicted based on the time elapsed since the preceding mass killing. Mass killings could be called random if the amount of time since the last mass killing gave no indication of the remaining amount of time that would pass before the next mass killing event. In stochastic processes, this property is called memorylessness. To illustrate this property, consider two scenarios: one in which the last public killing event occurred five days ago, and one in which the last public killing event has just occurred; one implication of the memoryless property is that the probability that the next public killing will occur within the next ten days is equal in both

http://www.ingentaconnect.com/content/springer/vav/pre-prints/content-vv2017-jul_a4_king_d_001-010 scenarios. Hence, the results of the uniformity and interarrival tests provided in Table 1 show that the stochastic processes composed of the mass killings in each of these six categories appear to occur randomly over time, such that the next mass killing event does not become more or less imminent as the last mass killing event recedes into the past.

4. Limitations and Future Work

While results presented in this article yield insights into the rate at which mass killings have occurred from 2006 to 2016, these results are limited in several ways. First, these analyses are restricted to observed events, and hence, cannot quantify the impacts of the successes of law enforcement officers in preventing such events or laws intended to deter potential perpetrators. Second, while two of these classifications consider mass killings using a particular kind of weapon, the corresponding conclusions cannot be extrapolated to comment on more general trends in violent crimes involving these weapons. For example, while the results presented in this article suggest that the rate of mass shootings has not increased over the past ten years, these analyses do not imply that other violent crimes involving firearms have also remained stable, nor do they suggest that this rate has either increased or decreased. Finally, the conclusions drawn in this article reflect data summarizing mass killings over the ten years between January 1, 2006 and October 4, 2016, and hence, care should be taken when extrapolating these conclusions outside of this time period.

From a data perspective, these analyses are limited by the availability and accuracy of data describing observed mass killing events. While the number of observed events in each category is sufficiently large for statistical analysis, improperly classified events could skew these results

http://www.ingentaconnect.com/content/springer/vav/pre-prints/content-vv2017-jul_a4_king_d_001-010 and lead to incorrect conclusions. Similarly, these results are sensitive to the conditions used to classify events as mass killing events. Following from FBI classifications, USA Today defines a mass killing as one in which at least four victims are killed during a relatively short period of time. However, there is not unanimous agreement on an appropriate definition of a mass killing (Huff-Corzine et al. 2014); applying different criteria for classifying mass killing events, such as raising or lowering the minimum number of victims, could lead to different results.

While the analyses presented in this paper examine a number of subsets of the mass killings in an attempt to consider mass killing events that are more homogeneous, other subsets can also be considered in future studies. For example, mass killings could be divided according to other features, such as geographic regions, socioeconomic characteristics, or number of victims to investigate whether mass killings exhibiting these common traits appear to take place randomly over time. More generally, as policymakers and the general public seek to better understand the causes and trends of mass killings in the United States, comprehensive data collection is a critical cornerstone of any statistical analysis of these events. While this paper has performed analysis on a large set of mass killing data published by USA Today (2016), the exhaustiveness of these data cannot be guaranteed. In the future, the collection and maintenance of a comprehensive data set of all mass killing events and their characteristics will be needed for researchers to glean more insightful lessons about these events.

5. Conclusions

With the recent increase in public awareness of mass killings in the United States, and a recent study has shown that the United States appears predisposed to public mass shootings when

compared with the other countries (Lankford 2016), it is critical that mass killing events be examined to understand patterns in how they occur. This article examines how different kinds of mass killing events occur over time using data documenting 323 mass killings observed from January 1, 2006 to October 4, 2016. The distribution of these mass killings over time does not differ significantly from a uniform distribution, suggesting that the rate of mass killings has remained stable over this ten-year period. However, the distribution of interarrival times (i.e., the time elapsed between consecutive mass killings) for these mass killings does differ significantly from the exponential distribution, suggesting that these interarrival times do not exhibit the memoryless property associated with the exponential distribution. This conclusion is consistent with an earlier study that found a contagion effect among mass killing events from 2006 to 2013 (Towers et al. 2015).

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By segmenting these mass killings based on the method or type of killing, the analyses presented in this article also examine more homogenous sets of mass killing events to assess whether mass killing events in the same category appear to be uniform and temporally random. The results of these analyses indicate that each category of mass killings events is statistically indistinguishable from a Poisson process, implying that their occurrences are random in the sense that their distribution over this ten-year timeline appears uniform, and that the time elapsed since the last mass killing does not provide any insight into the time until the next mass killing will occur. This conclusion differs from an earlier study suggesting that active shooter events increased in frequency between 2000 and 2012 (Blair et al. 2014). This difference suggests that there are fundamental differences between trends in active shooter events and mass killing events; such a difference is not surprising since, as discussed in Section 1, active shooter events and mass

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killing events are defined differently. The randomness of each category of mass killings also contrasts with recent findings that hate crimes tend to be clustered over time (King and Sutton 2013); a key distinction between these two findings is that multiple hate crimes may be set in motion by a single triggering event, while mass killings may be more isolated in nature.

These observations can help policymakers understand how mass killings occur, allowing them to make more informed resource allocation decisions when planning their response to future mass killing events, while also putting recent attention to mass killings in appropriate context. For example, while public killings such as those in Aurora, CO, and Newtown, CT, tend to receive significant media attention, public killings make up 16% (52/323) of mass killing events, while 53% (172/323) are classified as family killings. Regardless of the classification (e.g., public or family killing), each category of mass killing appears to occur at a stable rate. However, the relatively small aggregate rate of mass killings, with approximately one occurring nationally every two weeks across all categories, implies that preventing mass killings at every possible target would be very costly; Golany et al. (2009) explores optimal policies for distributing defense resources among sites under threat by probabilistic (e.g., random) or strategic adversaries.

Given a resource budget for a particular site, one-time expenditures that impede or delay public mass killings that are carried out, in concert with effective rapid-response interventions that can quickly interrupt such events over a wide geographic area, may be an efficient use of resources. This approach aligns strongly with existing recommendations by the New York City Police Department for active shooter events, which emphasize infrastructure-based responses and

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interventions that can delay an active shooter until law enforcement can respond (New York City Police Department 2012). More in-depth analysis of geographic trends in public mass killings could better assess how these resources should be spatially distributed.

However, such infrastructure-based responses are unlikely to have an impact on family killings, which are less likely to occur in a public place; this shortcoming is problematic, as family killings composed more than one-half of all mass killings in the United States from 2006 to 2016. While the present study suggests that one family killing does not trigger additional family killings, this result does not provide particular insight into how such killings can be prevented. Existing studies have investigated the potential psychological (e.g., Malmquist 1980, Liem and Koenraadt 2008, Liem and Reichelmann 2014) and financial (e.g., Liem et al. 2013) causes of family killings; addressing such root causes remains a critical step in preventing family killings. However, preventing family killings, or any mass killing, is a complex issue and it is unlikely that a single type of intervention will address all occurrences (Fox and DeLateur 2014). Nonetheless, the current study provides insight into the temporal distribution of these events, with their temporal uniformity and randomness suggesting that a recently-occurring family mass killing does not indicate that another is more or less likely to occur than normal.

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