# COLLECTIVE VIOLENCE AND HETEROGENEOUS DIFFUSION PROCESSES: U. S. RACIAL RIOTING FROM 1964 TO 1971

**Daniel J. Myers**
University of Notre Dame

**Abstract**

This analysis of the diffusion of racial rioting in the United States applies recently-developed extensions of event history analysis to the spread of rioting from 1964 to 1971. Contrary to early analysis of riot diffusion, the results demonstrate that diffusion is a critical force behind the pattern of rioting. The analysis identifies several types of diffusion in the riot cycle and demonstrates that contagious influence from riots decays over time, is mitigated by geographic distance, and is conditional on the severity of riots. Methodologically, the analysis produces extensions of prior event-history diffusion models which allow their use with collective violence data.

Author Note: This research was supported by grant SBR 96-01409 from the National Science Foundation. I thank William Feinberg, Alexandra Corning, Gerald Marwell, Alberto Palloni, Lawrence Wu, and Pamela Oliver for comments on earlier drafts, Gregg Carter for providing his riot data, and Victoria Myers for assistance locating and retrieving original data.

Biographical Note: Daniel J. Myers is Assistant Professor of Sociology, University of Notre Dame, 325 O'Shaughnessy Hall, Notre Dame, IN 46556, (219) 631-3839, Myers.33@nd.edu, http://www.nd.ed/~dmyers. His current interests are in diffusion models for collective behavior, game theory, and racial rioting.

## INTRODUCTION

In the mid-1960s, a new wave of collective protest was developing in the United States just as civil rights movement activity began to decline (McAdam 1982; Jenkins and Eckert 1986). This wave of protest was to shock the United States as thousands of Black Americans took to the streets in an unprecedented wave of rioting resulting in massive property damage, hundreds of injuries, and scores of deaths at the hands of the police. The magnitude of the rioting shocked White America and turned the attention of the federal government and many scholars to the cause of the rioting. The extensive body of literature which resulted cannot be summarized here, but in large part is inconsistent with regard to its conclusions about the causes of the rioting. Answers to questions of why rioting occurred where it did and when it did have proven particularly thorny as evidence from a number of schools of thought has been alternately presented and refuted in a long series of studies (for examplars and reviews, see National Advisory Commission on Civil Disorders 1968; Leiske 1978; Spilerman 1970a; 1971; 1972; 1976; Mazur 1972; Carter 1986; Jiobu 1971; Stark, et al. 1974; Morgan and Clark 1973; McElroy and Singell 1973; McPhail 1994; McPhail and Wohlstein 1983; Myers 1997; Olzak and Shanahan 1996; Olzak, Shanahan, and McEneaney 1996).

Although a massive amount of attention that has been paid to the topic, systematic study of how the rioting spread across the U.S. has been a neglected issue. Attempts to understand the spread of violence either have been incomplete, or have focused on a narrow subset of the riot data, thus limiting the conclusions we can draw about the general process of riot diffusion (Spilerman 1970a; 1972; Stark, et al. 1974). The present study seeks to partially redress this omission. By bringing recent event history diffusion models to bear on data encompassing the entire rise and fall of the riot wave, this paper not only develops a richer understanding of how rioting spread during the 1960s and early 1970s, but also demonstrates a general approach for examining contagion processes in collective violence waves.

Despite our lack of understanding of riot diffusion in the 1960s, both the study of spread of collective behavior and of diffusion processes more generally have substantial academic histories (see McPhail 1991, Turner and Killian 1972; Rogers 1995; Mahajan and Peterson 1985 for reviews). Beginning with Le Bon's ([1895] 1960) view of collective behavior as a process of psychological contagion, diffusion processes have long held the interest of social psychologists of collective behavior (McPhail 1991 provides a thorough review). These early notions of "madding" crowds have been thoroughly debunked, resulting in a fundamental change in the approach to studying the diffusion of collective behavior. First, analyses are now focused on the spread of events rather than the spread of action through individuals in a crowd (e.g., Olzak 1992; Spilerman 1970a; Rudé 1964). The more fundamental change, however, is the conception of diffusion as a social learning process in which rational assessment of the outcomes of others' actions leads to either adoption or abandonment of the form of action. It is this mechanism of rational action that is thought to drive the clusters or cycles of collective behavior typically observed across many movements (Oberschall 1989; Oliver 1989; Pitcher, Hamblin, and Miller 1978; Tarrow 1994; Olzak 1987; Koopmans 1993).

The results in this paper support this rational actor view of collective violence diffusion and provide an interpretation of the patterns of rioting during the 1960s congruent with it. A number of previously undiscovered diffusion processes are located in the data. Specifically, three different levels of collective violence waves are detected, contagious influence is shown to decay over time and to decay over distance, and riot severity is found to be a major contributor to the diffusion process.

## DIFFUSION AND COLLECTIVE VIOLENCE

Social diffusion processes are those in which the adoption of a behavior by one actor affects the likelihood of adoption by other actors in the social system (Rogers 1995; Strang 1991a). Diffusion processes require contact between "contagious" adopters and those who have not yet adopted. In social diffusion processes this contact comes in the way of communication which travels according to established social networks (Hamblin, Jacobsen, and Miller 1973; McPhail and Wohlstein 1983). These social networks may be defined by friendship circles, professional acquaintance structures, market practices, transportation routes, or family ties (Coleman, Katz, and Menzel 1966; Rudé 1964; Charlesworth 1979; Morris 1984; Spilerman 1970a; Oliver 1989). Whatever way information about some practice is shared, it provides a potential web for diffusion to traverse. All people in the social network who share some fundamental similarity related to the diffusing practice are potential adopters (Strang and Meyer 1993). Often, however, information about innovations travels through less specific routes when events or "adoptions" are announced through the mass media (Oberschall 1989). Rather than a series of lines connecting individuals, the initial effect of mass media might better be viewed as a concentric area around its origin. This area of influence is simply defined by the range of the medium's distribution. For example, most newspapers have relatively concentrated distribution areas as do radio and local television broadcasts.[1] These communication networks predict specific diffusion patterns that will be examined in this paper.

As potential adopters receive information through the communication network about the behavior of prior adopters, they attempt to assess the outcomes for those actors. Based on their own assessment of these outcomes, potential adopters will decide to adopt if it appears that (1) the prior adoption proved to be more effective than other accessible alternatives and (2) the potential adopter will experience similar outcomes upon adopting the behavior (Oberschall 1989; Rogers 1995; Fliegel and Kivlin 1966). Thus, structural similarities among actors will accelerate diffusion because the more congruent the situation of prior and potential adopters, the more likely that the outcomes for earlier adopters will match the outcomes for later adopters. Structural similarity thus enhances the certainty with which potential adopters can predict the consequences of adoptions.

**Heterogeneity in Diffusion Processes**

Using these basic components of rationality, structural similarity, and communication through social networks, scholars from a variety of disciplines have constructed a multitude of models describing and predicting diffusion (see Rogers 1995; Mahajan and Peterson 1985; Coleman, Katz, and Menzel 1966; Burt 1987; Strang and Tuma 1993). While many of these models are generic and can be reasonably applied to many social phenomena, others are more limited in scope as they attempt to model the spread of a specific process in a specific historical context (e.g., Rudé 1964; Charlesworth 1979). Among the models with a more general orientation, most suffer from a number of untenable assumptions which limit their applicability for virtually any social process. In particular, standard diffusion models assume both <u>temporal</u> and <u>spatial</u> homogeneity (Strang and Tuma 1993). Models assuming spatial homogeneity treat all actors in the social system (adopters, potential adopters, and non-adopters) as if each has the same level of contact with all other members. Temporal homogeneity treats each adoption as if it maintains the same level of influence on non-adopters through time.

Suppose one were studying the diffusion of home computers. Spatial and temporal homogeneity would require that a person purchasing a computer three years ago at a location 2000 miles away from a potential first-time computer buyer will have the same influence as if his or her next-door neighbor had purchased one the month before. Given the relative probability of contact between the two pairs of actors, we can easily see that these assumptions rarely hold for social processes. Quite simply, social communication networks are geographically concentrated. Friendship networks, family circles, work relationships, and even mass media have more influence locally than they do elsewhere.

Most diffusion models exhibit these limitations because they model the process on the population level. These models attempt to account for over-time changes only in the cumulative number of adopters and non-adopters (Mahajan and Peterson 1985). Because of the severely limited application of models

---

[1] There are growing exceptions to these limitations, however, as networked stations transmit information over much broader areas.

assuming spatial and temporal homogeneity, scholars have recently begun to develop approaches that relax these assumptions (e.g., Berry and Berry 1990). In particular, Strang and colleagues (Strang, 1990; 1991a; 1991b; Strang and Tuma 1993; Greve, Strang, and Tuma 1995) have demonstrated that event history models provide not only a natural method for examining diffusion processes,[2] but also allow for the inclusion of both spatial and temporal heterogeneity in diffusion models. Because event history techniques allow analysis of individual risk levels and can easily incorporate time-varying covariates, they permit an examination of both the relative spatial positions of individual actors and the decay of influence over time.

Formally, an event history analysis models the hazard rate of adoption:

$$l(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t | t \leq T)}{\Delta t} \tag{1}$$

where $T$ is the time of the event and $\lambda(t)$ is the hazard rate. In other words, the instantaneous hazard rate for an individual is a function of the probability that an event will occur to the individual between $t$ and $t + \Delta t$, given that it has not yet occurred at time $t$. For the present study, the hazard rate is the instantaneous probability that a riot will occur in a given city, given that the city is at peace as it enters the date in question.

Translating standard diffusion models to the event history framework produces

$$l_n(t) = a_n + bs(t) = a_n + \sum_{i \in \mathbf{S}(t)} b \tag{2}$$

where $n(t)$ indicates the potential adopters (all those in the risk set **N** at time $t$), $\mathbf{S}(t)$ is the set of prior adopters (spreaders at time $t$), $a$ is the effect of intrinsic factors, and $b$ is the contagion effect from all those who have adopted by time $t$ (see Strang and Tuma 1993; Mahajan and Peterson 1985 for more detail). It is the structure of $b$ which is the focus of attempts to incorporate both temporal and spatial heterogeneity into the diffusion model. A number of approaches to contagion can be incorporated into the definition of $b$ including historical time (Strang 1990), time since the most recent event (Strang 1991b), measures of social proximity (Strang and Tuma 1993; Greve, Strang, and Tuma 1995; Myers 1997; Hedström 1994), and measures of infectiousness and susceptibility of the sets of actors (Strang and Tuma 1993; Greve, Strang, and Tuma 1995). When event history models are calculated, the logarithm of the rate is modeled in order to permit only positive hazard rates (Tuma and Hannan, 1984). Therefore models estimated herein follow the multiplicative form presented by Strang and Tuma (1993):

$$l_n(t) = \exp\left[ a_n + \sum_{i \in \mathbf{s}(t)} b \right]. \tag{3}$$

**Modeling Fundamental Diffusion Processes**

Standard diffusion models estimated in the current context would predict that the rate of adoption is a function only of intrinsic characteristics and the number of prior adopters. Thus, a standard diffusion model is represented as

$$l_n(t) = \exp\left[ \boldsymbol{\alpha} \mathbf{x}_i + \beta \sum_{j \in \mathbf{I}} q_{j,t-1} \right] \tag{4}$$

where $\alpha$ is a vector of coefficients indicating the effects of individual or intrinsic characteristics represented by vector $\mathbf{x}_i$, $\beta$ is effect of the diffusion term, and $q$ is a dummy variable indicating whether actor $j$ has adopted the behavior at time $t$-1 (for a related approach see Hedström, 1994). Although some analyses

[2] In addition to the network diffusion studies conducted by Strang and others, event history diffusion models have proven particularly useful for tracking the diffusion of governmental policies (e.g., Berry and Berry 1990; Mooney 1997; Mooney and Lee 1995; Minttom 1997; Soule and Zylan 1997).

intended to capture diffusion effects have used analogous models (Strang 1990; Strang 1991b, Soule and Zylan 1997), it should be recognized that detecting a linear effect is not necessarily adequate to demonstrate congruence between the data and standard diffusion models. Typical diffusion models posit that the cumulative number of adopters should follow a sigmoid pattern over time (Rogers 1995, Rogers 1986, Mahajan and Peterson 1985; Valente 1995). As in Figure 1 Panel A, the process begins slowly, followed by a take-off period, and eventually wanes as the set of potential adopters is depleted. This means that the probability of new adoption over time should follow the derivative of the cumulative adopter curve (Figure 1 Panel B). When we model the probability of new adoption as in the models above, we should find that the linear relationship between cumulative adopters and the new adoption rate is essentially zero. This is made apparent by the curves in Figure 1. As the cumulative number of adopters rises, the rate of new adoption increases during the first half of the process, but declines during the second half.

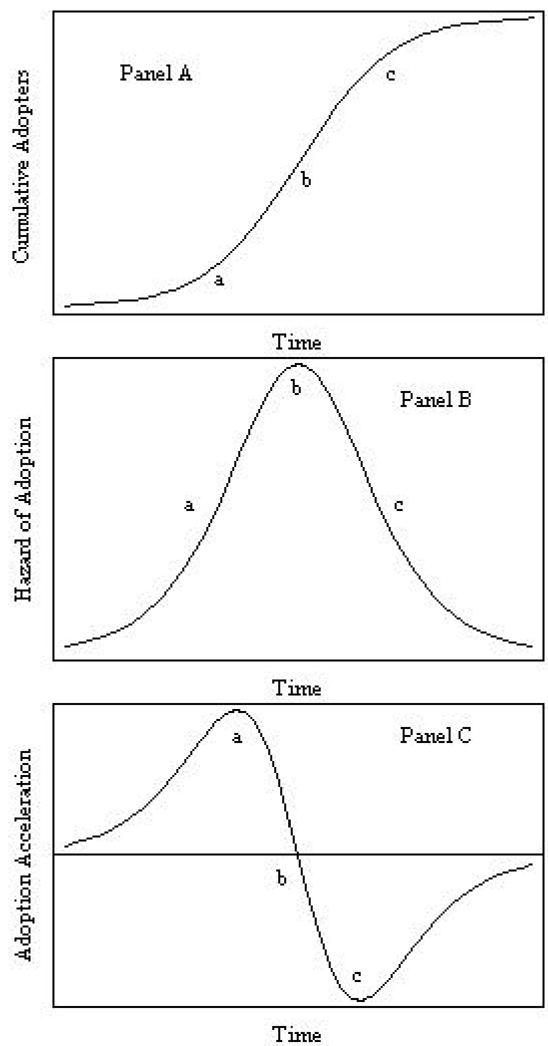



**Figure 1: Predicted adoption patterns based on internal diffusion models**

Analyses that have used such a process however, have detected significant linear effects. The reason is simply that these analyses have been limited to the upswing of the diffusing behavior (see Strang 1990; Strang 1991b). If the temporal limitations (either of the study or due to historical reasons) truncate the process before it is complete, the likelihood of detecting a linear trend increases. The meaning of this trend for demonstrating diffusion however, is questionable. In effect, an increase in the probability of adoption predicted solely by the number of prior adopters means only that the process is on the rise. Because processes distinct from internal diffusion models can cause such a rise, compatibility with diffusion models is not necessarily demonstrated.

In order to demonstrate congruence with a standard diffusion model, a polynomial model must be calculated to capture the curvilinear trend. In order to match diffusion models the rate data must not only reveal an inverted "V" shape (Figure 1, Panel B), but must also reflect the inflection points of the curve. These inflection points are more apparent when we examine the second derivative of the cumulative adopter curve or the adoption acceleration curve (Figure 1 Panel C). Here it is clear that the adoption accelerates from time zero up to point *a*, then decreases through point *b* where it becomes negative, reaches its lowest level at point *c* and then returns to zero. These patterns can be captured by a second-degree polynomial in the event history diffusion model by

$$l_n(t) = \exp\left[\boldsymbol{\alpha}\mathbf{x}_i + \beta_1 \sum_{j \in \mathbf{I}} q_{j,t-1} + \beta_2 \left(\sum_{j \in \mathbf{I}} q_{j,t-1}\right)^2\right]. \qquad (5)$$

If the indicated pattern is found in the data, the coefficient estimating $b_1$ will be positive and $b_2$ will be negative.

**Collective Violence**

Due to fundamental differences between collective violence and the behaviors to which diffusion models are ordinarily applied, the direct application of innovation diffusion models to the phenomenon of collective violence is not completely straightforward. Nevertheless, careful attention to the characteristics of collective violence can lead to an informative marriage of diffusion models and collective violence phenomena. The core characteristic of collective violence that prevents direct portability of diffusion models is its short-lived nature. In the vast majority of diffusion models, once the actor adopts a behavior, she or he is, from that point forward, considered a continuous adopter. It is assumed that following adoption, at each opportunity to exhibit the behavior, the adopter will do so. Whether the behavior is prescribing a new drug (Coleman, Katz, and Menzel 1966), adoption of a new agricultural technology such as tractors or hybrid corn (Hagerstrand 1953; Griliches 1957; Casetti and Semple 1969), the institution of a new governmental policy (Berry and Berry 1990; Soule and Zylan 1997), or the formation of unions (Hedström 1994), continuous and irreversible adoption is assumed.

The assumption of permanent adoption is useful because it considerably simplifies analysis and furthermore is often a reasonable position. While is it possible that those who begin to use tractors on their farms may abandon them or that once unions form they will disband, these cases are relatively rare. Even in those cases in which a diffused technology is later replaced through the diffusion of a more advanced one, such a process does not usually occur within the time frame used to examine the spread of the original process. When the assumption of permanent adoption is reasonable, analysts only need to concern themselves with the first instance of the behavior for each actor. In event history analysis, only the time of initial transition from **N**(*t*) to **S**(*t*) is required to calculate adoption rates.

Collective violence does not often follow the typical diffusion of innovation pattern, however. Because collective violence such as rioting tends to appear briefly, disappear for a time, and then reappear, the continuous adoption assumed by most diffusion models clearly is not present in almost all waves of collective violence. In the current case, among all cities that experienced rioting from 1964-1971, there were a total of 914,586 city-days available for rioting. But rioting was present on only 1802 city-days (0.20 %). Even during 1968, the year of heaviest rioting, of 114,558 city-days available, only 738 (0.64 %) were occupied by rioting. Thus, even in a period marked by extremely high levels of collective violence, the assumption of continuous adoption is untenable.

Furthermore, this substantial incompatibility between standard diffusion models and collective violence means that an event history analysis using only the first adoption would produce an inadequate representation of the diffusion process. Following such a procedure leads immediately to a loss of data if any actor (city) experienced more than one event (riot) during the study period. The significance of this loss of data depends, in part, on the number of events eliminated. In the current analysis, it amounts to a huge loss. As detailed in Table 1, of the 313 cities included in the study, 153 experienced only one riot, but 160 others experienced more than one riot. If only the first riot occurring in each city were analyzed, only 313 of the 752 riots that occurred from 1964-71 would be included. Despite this fundamental difference between collective violence and other diffusion phenomena, event history analysis still provides an attractive avenue for analysis. To incorporate all riots in all cities, each city is viewed as entering a new risk episode following the termination of a riot. Thus each city contributes R + 1 risk episodes, where R is the number of riots occurring in that particular city. Special considerations for estimating such models are discussed below.[3]

Table 1: Distribution of Riots in the US, 1964-1971

| Number of riots (k) | Number of cities experiencing k riots | Total number of riots |
|---|---|---|
| 1 | 153 | 153 |
| 2 | 61 | 122 |
| 3 | 41 | 123 |
| 4 | 24 | 96 |
| 5 | 11 | 55 |
| 6 | 4 | 24 |
| 7 | 6 | 42 |
| 8 | 5 | 40 |
| 9 | 3 | 27 |
| 10 | 1 | 10 |
| 11 | 1 | 11 |
| 14 | 1 | 14 |
| 16 | 1 | 16 |
| 19 | 1 | 19 |
| Sum | 313 | 752 |

The phenomenon of collective violence does, however, share much with standard diffusion processes. Specifically, the general trend of the rate of adoption follows a pattern typical to diffusion processes. The number of additional adoptions is initially very low, eventually increasing to a maximum, and then tapering until adoption virtually disappears. The cumulative count of these adoptions (or riots) produces the typical sigmoid pattern so common to diffusion processes (Pitcher, Hamblin, and Miller 1978; Mahajan and Peterson 1985). Figure 2 shows the yearly count of riots (new adoptions) and the cumulative count of riots from 1964-1971. The sigmoid pattern of the cumulative riot count is apparent.

[3] The importance of riot severity in predicting diffusion patterns (detailed below) provides additional justification for using repeated events analysis rather than limiting the focus to the first riot in each city. Because the size of the non-White population is significantly related to both severity (Spilerman 1976; Carter 1983; 1986) and to the number of riots (Spilerman 1970), eliminating the second and subsequent riots in each city tends to eliminate riots in cities with higher Black populations and therefore more severe riots. Such a procedure therefore would introduce bias with regard to the effect of severity on the diffusion of rioting.

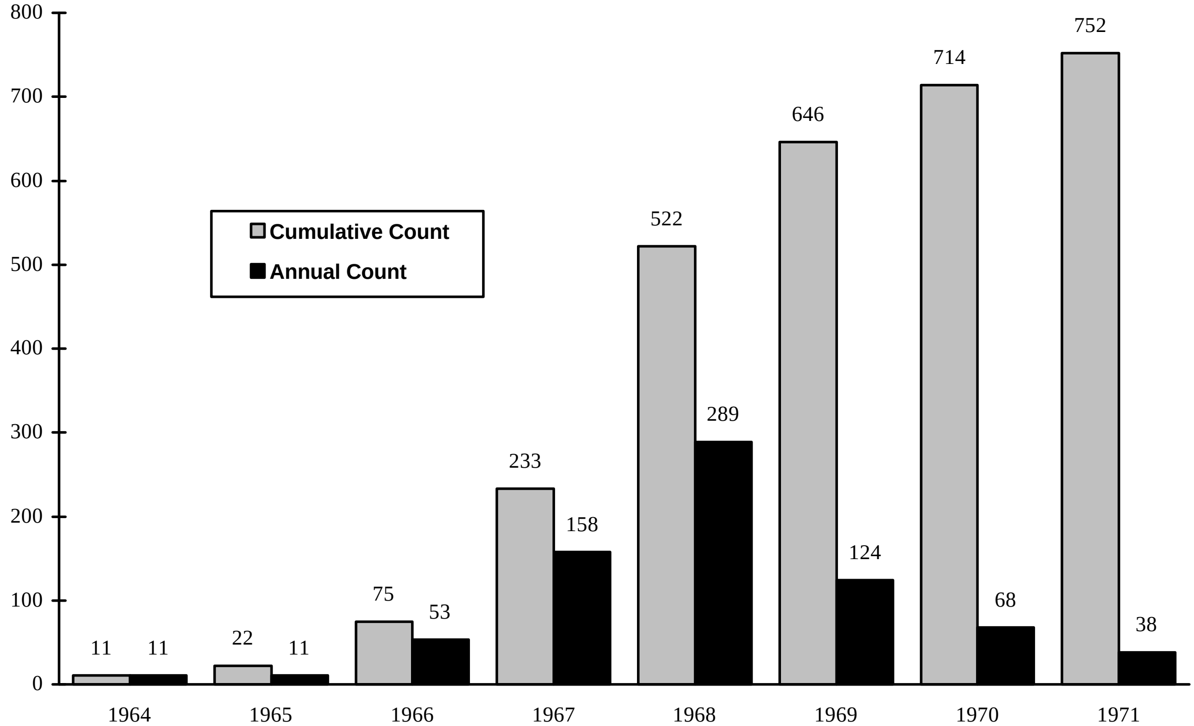



**Figure 2: Rioting by Year, 1964-1971**

Nevertheless, the interpretation of this pattern must differ for collective violence processes. First, most diffusion models function under the restriction that the number of adoptions equals the number of adopters. When approaching collective violence on the event level and the unit of analysis is a city or group, it is clear that the number of adoptions often far exceeds the number of adopters. Second, the decline of adoption in standard diffusion models results from the total population of potential adopters becoming saturated. The cycle of adoption must necessarily decline as $n(t)$ approaches its lower limit and $s(t)$ approaches its upper limit. In the case of collective violence and other disruptive protest activity, there is no such shortage of potential adopters. Because of the short-lived nature of collective violence, all actors are almost constantly at risk of adoption. Adoption does allow actors to move out of $\mathbf{N}(t)$, but only momentarily. Thus the decline of adoption must be viewed differently. Rather than waning numbers of potential actors, the ebb of a riot cycle is seen as an abandonment of the rioting as a mode of collective behavior.

A second inconsistency between collective violence and standard diffusion models is that while collective violence may appear to have a fairly continuous pattern when events are aggregated at the annual level, patterns within the cycle reveal a process that is far from smooth and continuous. Diffusion processes for disruptive or violent collective action are different from non-disruptive or non-violent action because they are subject to explicit repression attempts by the authorities, a variety of social sanctions, and simple exhaustion through the inevitable tiring and calming of participants (Kelly and Isaac 1984; Koopmans 1993; Oberschall 1978; Oliver 1989). As a result, collective violence is characterized by series of mini-cycles which accelerate and then decline. Because diffusion is likely to occur in these mini-cycles as well as in the larger wave of action, complete mapping of the diffusion of collective violence requires careful attention to these waves within waves.

**More Complex Models of Contagion**

To develop a thorough understanding of how collective violence and rioting can spread, adjustments to standard diffusion models reflecting the above concerns must be introduced. In this section, I formally define a variety of contagion measures which represent hypotheses about various diffusion processes. Reflecting the above discussion, I first adjust the model described in equation (4) to allow single actors to adopt repeatedly. Second, I extend basis of equation (5) to recognize seasonal waves within the larger riot wave. Third, unlike previous analyses (Strang 1990; 1991b; Rasler 1996) which depend solely on counts of previous events as the predictors of diffusion, I incorporate both temporal and spatial heterogeneity among prior events to predict diffusion. Finally, I consider the possibility that heterogeneity in the intensity of adoption further contributes to differences in contagion. To simplify the presentation, I focus on the total contagion experienced by a given actor at a given time (denoted $c_{it}$). The method of estimating $c_{it}$ (below), treats each variant of $c_{it}$ as one element in the vector $\mathbf{c}_{it}$ which estimates the effects of a set of internal diffusion variables.

***Aggregate Patterns.*** The first required adjustment to standard diffusion models is to permit repeated adoptions by the same actor to be considered as separate adoption events. To make this adjustment, contagion indicators must be calculated using the set of adoptions rather than the set of adopters. This alteration of equation (4) produces

$$l_n(t) = \exp[\boldsymbol{a}\mathbf{x}_i + \boldsymbol{b}\mathbf{c}_{it}], \qquad c_{it} = \sum_{a \in \mathbf{A}} q_{a,t-1} \tag{6}$$

where **A** denotes the set of all adoptions, $q$ is a dummy indicating if adoption $a$ occurred by time $t$-1. Thus in this simple model, the total contagion experienced by any actor $i$ at any time $t$ is simply the sum of all riots which occurred at time $t$-1 or earlier. This measure is straightforwardly substituted in equation (5) to account for predicted curvilinear trends in adoption.

While most diffusion models suggest a relatively smooth aggregation of adoptions (even for violence and rioting, see Pitcher, Hamblin, and Miller 1978; Hamblin, Jacobson, and Miller 1973; Midlarsky 1978), this is not the case for empirically observed waves of collective violence. In addition to the mini-cycles discussed above, seasonal variations in adoption rates are apparent within the racial rioting of the 1960s. Quite simply, rioting is an outdoor activity and is far less comfortable for participants in the winter months. Each year we expect to observe a lull in rioting during the winter and a peak during the summer (Baron and Ransberger 1978). This cycle produces a sigmoid pattern of cumulative adoptions within each year. To detect this effect and to control for weather-related time dependency, I include a yearly version of the cumulative riot count. Because I wish to estimate the effect with a single variable and the number of events varies from year to year, it is necessary to adjust the yearly count by dividing by the total number of events for that year, producing the cumulative proportion of events for that year rather than the raw event count:

$$c_{it} = \frac{\sum_{a \in \mathbf{A}(t_y)} q_{a,t-1}}{\sum_{a \in \mathbf{A}(t_y)} 1} \tag{7}$$

Here, $\mathbf{A}(t_y)$ is the set of all adoptions which occurred during the current year, $q$ is a dummy indicating if adoption $a$ occurred by time $t$ - 1. Because the pattern of rioting within a year cycles following the sigmoid diffusion pattern, a second-degree polynomial analogous to equation (5) is required.[4]

[4] Incorporating variables capturing the effect of the overall accumulation of riots and the yearly accumulation of riots effectively controls for historical time because the cumulative number of riots is

***Temporal Heterogeneity: Does Contagious Influence Decay over Time?*** The assumption of temporal heterogeneity requires that all adoptions have constant effects on potential adopters over time. Although some adopted behaviors may place continuous press on others to adopt, the assumption is particularly implausible in the case of collective violence. Because rioting terminates after a few days, riots which ended long ago are unlikely to have as much influence as those that ended within the past week or are still underway. Adequate modeling of riot contagion requires allowing the contagion effect to decay over time. One simple model of decay would allow riots to have a constant effect for a short period of time and then to have no effect.[5] Thus the model assumes that once more than one week has passed since a riot outbreak, the riot no longer contributes to future outbreaks (beyond that effect which is captured by the overall trend variables). This model is represented by:

$$c_{it} = \sum_{a \in \mathbf{A}} m_{T(a), t-7 <= T <= t-1} \tag{8}$$

where **A** is the set of all adoptions and *m* is a dummy indicating if the time *T* of adoption *a* occurred at least one day before the current time *t* and at most seven days before time *t*. At its core, this model suggests that only the total number of riots that occurred in the previous week is important to capturing the diffusion effect.

While equation (8) is attractive in its simplicity, a more sophisticated model would suggest that the effect of a riot decays gradually as time passes. The current analysis tests for this effect using

$$c_{it} = \sum_{a \in \mathbf{A}} \frac{m_{T(a), t-7 <= T <= t-1}}{t - T(a)} \tag{9}$$

where the denominator is the amount of time elapsed since the occurrence of adoption *a*.

***Spatial Heterogeneity: Does Contagious Influence Decay over Distance?*** Under the models presented so far, all actors are assumed to have an equal effect on each other. Given that contagion is passed by contact, this assumption of homogenous mixing means that all actors in the system have an equal probability of contact. With regard to rioting, several modes of contact are possible (Morris 1984; Oliver 1989). Information about collective action may be transmitted through friendship and relative networks via direct face-to-face contact or by way of telephone. Obviously, these types of contact networks are highly geographically concentrated and are clearly not subject to homogenous mixing. Perhaps the most important communication channel with regard to the rioting of the 1960s, however, was the mass media (Spilerman 1970a). And because rioting was a national problem and national attention was focused on the riots, a variant of the homogenous mixing idea is more plausible here than in many waves of collective action. If all rioting were given enough coverage by national media, the spread of information about rioting

---

highly collinear with time. Models which include cumulative riot count variables were also calculated adding historical time indicators, but time indicators did not add to the predictive power of the models due to their high collinearity with the baseline diffusion variables, and thus these results are not detailed herein.

[5] Because allowing riots to decay eternally makes calculating models very cumbersome, the current analysis limited the influence of riots to two weeks following the initial outbreak. Although this decision was somewhat arbitrary, it seems reasonable in light of other analyses of collective violence which have shown that waves of violence tend to cycle in relatively short periods of time (Olzak,1987; National Advisory Commission on Civil Disorders 1968; Myers 1997). Two different versions of contagion variables were introduced, one allowing decay over one week and one allowing decay over two weeks. Because the two-week version of all contagion variables contributed nothing to predicting riots beyond what was detected by the one-week version, only the one-week versions are presented herein.

would effectively be constant across the U.S. and thus no differences based on distance would be expected. If, however, coverage of rioting were more concentrated in the region where it occurred, spatial homogeneity would not be supported. Following analyses by Hedström (1994) and Myers (1997) then, I incorporate test for spatial heterogeneity with a decay function reflecting the distance between adopters and potential adoptors:[6]

$$c_{it} = \sum_{a \in \mathbf{A}} \frac{m_{T(a),t-7<=T<=t-1}}{\left(t - T(a)\right)} d_{ij(a)} \tag{10}$$

where *d* is a function of distance between city *i* and the city in which adoption *a* occurred, *j*(*a*).[7]

***Contagious Influence and Riot Severity.*** Beyond temporal and spatial heterogeneity, there are other elements of heterogeneity within the diffusion process which can propel or impede diffusion. One of these elements is the nature of the individual act of adoption.[8] While it has been shown in a number of studies that characteristics of individuals who adopt can increase adoption by others (Burt 1987; Coleman, Katz, and Menzel 1966), the characteristic of the adoption act has been neglected. In particular, it seems likely that the vigor with which the adopter takes on the new behavior affects the contagiousness arising from their adoption act. If, when adopting a new seed, the farmer decides to plant all of her fields with new seed, we would expect her adoption to have more influence than if she chose to use the new seed on only a small fraction of her land. Similarly, a doctor who simply adds a new drug, as one of many, to his repertoire is likely to have less influence on other potential adopters than one who prescribes the new drug at every possible juncture.

Such is the case with collective violence. The intensity of a riot is likely the most important factor driving how much coverage it receives from the mass media (Snyder and Kelly 1977). This coverage in turn determines how infectious the riot will be. Therefore, it is reasonable to expect that riots that are more severe (as measured by property destruction, harm to human life, duration, and so forth) will have a much stronger effect on future rioting than will less severe outbreaks. Furthermore, more severe riots will be contagious over larger geographic areas as more severe riots receive widespread media coverage. From this notion, a final contagion model is derived. It calculates contagion as a time-decaying function of severity:

$$c_{it} = \sum_{a \in \mathbf{A}} \frac{m_{T(a),t-7<=T<=t-1}}{t - T(a)} s_a \tag{11}$$

---

[6] Versions of equations (10) and (11) that did not permit time decay were also tested. Because the time-decaying versions subsumed the non-time-decaying version, the latter are not presented.

[7] The decay function used in these analyses is a weighted function of distance: $d_{ij(a)}$ = .998 exp[3.48/exp(.00252x) - 3.2/exp(.00265x) -.000128x] where x is the distance from *i* to *j*(*a*). The derivation and rationale for this function is given in Appendix A.

[8] Fliegel and Kivlin (1966) examined a number of characteristics of innovative behaviors that could affect adoption rates, including initial cost, payoff, regularity of reward, and complexity. Because only one type of collective action is examined herein, differences in these types of characteristics cannot be investigated in the current analysis. Compared to other types of collective action though, collective violence has some characteristics that are likely to accelerate its spread (for example, riots are dramatic and newsworthy) and others that slow its adoption (for example, violence entails risk, much effort, and a substantial break from life routines).

where $s_a$ is the severity of adoption $a$.[9]

## DATA

To provide a initial test for heterogeneity in the diffusion process as represented in the models above, I employ the wave of racial rioting which occurred in the United States from the mid-1960's through the early 1970's. A number of different data sets cataloging riots from this era have been constructed (Spilerman 1970b; Olzak and Shanahan 1996; Jiobu 1971) but the one collected by Gregg Carter (1983, 1986, 1990) is used herein. Carter tabulated all riots that occurred in the United States from 1964 through 1971 using a comprehensive set of published and unpublished riot compilations including the Congressional Quarterly's Civil Disorder Chronology, the New York Times Index, the Report of the National Advisory Commission on Civil Disorders, Brandeis University Lemberg Center for the Study of Violence's Riot Data Review, unpublished material from the Lemberg Center, the U. S. Senate's compilation reported in Riots, Civil, and Criminal Disorders, and original newspaper articles from the New York Times and the Washington Post.

Of the many civil disorders that occurred from 1964-1971, those identified as riots by Carter conform to the same conditions forwarded by Spilerman (1970a): Each incident must have involved at least thirty people and included some interpersonal violence or destruction of property. Furthermore, those riots that were focused on institutional conflicts (such as those in schools and union halls) and those that were not "spontaneous" (those that arose as a result of a planned protest or demonstration) were eliminated. Only incidents involving primarily Black aggression were included in the data.[10]

Using this method, Carter located 752 riots distributed across the 1964-1971 period as displayed in Figure 2. In the current analysis, I eliminate one riot and analyze a total of only 751. Two distinct riots occurred on July 18, 1964 in New York City, one in Manhattan and one in Brooklyn. Because computation is considerably simplified by assuming that no more than one riot could occur in a one city on a single day, I eliminated the riot which occurred in Brooklyn. Given this singular exception, the procedure is unlikely to have any substantive impact.

Compared to other data sets, Carter's has several distinct advantages which make it more comprehensive and thus superior for the analysis of riot diffusion. First, Carter's attention to detail and willingness to consult original newspaper sources (rather than simply relying on indexes or summaries constructed by others) identified many riots which where not detected in previous studies. For example, in 1968 alone, Carter identified 289 riots compared to only 141 detected by Spilerman (1970a; b) using the same selection criteria. Table 2 summarizes the details of several key studies of racial rioting and it is apparent that Carter's data are by far the most complete with respect to racial rioting in the 1960s period.

[9] These diffusion covariates were calculated for the analyses by the program DIFFCOV, which is available from the author.

[10] The rationale for all of these selection criteria received complete attention in previous analyses of the riot data (Spilerman 1970a; 1970b; Myers 1997; Carter 1983).

Table 2: Sample Characteristics of Key City-Level Analyses of the 1960's Racial Rioting

| Author(s) | Temporal Scope | Number of Cities Examined (Number that experienced riots) | City Population Lower Limit | Black (or Non-white) Population Lower Limit | Riot Size Criterion | Number of Riots |
|---|---|---|---|---|---|---|
| Carter 1983 | 1964-1971 | 313 (313) | no limit | no limit | 30 or more participants | 752 |
| Spilerman 1970; Spilerman 1976; Myers 1997 | 1961-1968 | 410 (169) | 25,000 | 1,000 | 30 or more participants | 341 |
| Jiobu 1971 | 1965-1969 | 74 (61) | 100,000 | Black population at least 85% of non-whites | Not stated | 162 |
| Lieske 1978 | 1967-1969 | 119 (93) | 50,000 | 1,000 | 4 or more participants | 334 |
| Olzak and Shanahan 1996 | 1954-1993 | 204 (86) | 204 largest cities | no limit | "large scale" (most had at least 50 participants) | 249 |
| Olzak, Shanahan, and McEneaney 1996 | 1960-1993 | 55 (43) | Sample of large SMSAs for which all covariate information was available | | 50 or more participants | 154 |

Furthermore, Carter did not restrict his attention to an arbitrary subset of cities as many previous analyses have (e.g. Spilerman 1970a; 1971; 1976; Myers 1997; Olzak and Shanahan 1996; Olzak, Shanahan, and McEneaney 1996; Jiobu 1971). Limiting analysis to these subsets of cities (based primarily on population size) was necessary because important structural covariates were not available for many of the smaller, excluded cities. The result, however, was that many riots were either ignored or not detected. For example, Spilerman's criteria for inclusion, a total population of 25,000 or greater and a Black population of 1,000 or greater, was one of the most inclusive, yet even these cause a significant bias. Contrary to Spilerman's (1970; 1971; 1976) claims, there were in fact many riots which occurred in cities either with Black populations of less than 1,000 or total populations of less than 25,000. Of the total 752 riots Carter located, 136 (18%) occurred in cities excluded from Spilerman's original data. These riots were far from a random subset. In general, these excluded riots occurred in smaller cities with smaller Black populations, were of lower intensity, and were more likely to be in the south than the riots included in the Spilerman studies (see Table 3 for details).

Table 3: Differences between Cities and Riots Included in and Excluded from Spilerman studies.[a]

| | Mean 1970 Total Population | Mean 1970 Black Population | Mean Riot Severity | Mean Latitude | Proportion in the South[b] |
|---|---|---|---|---|---|
| Excluded | 20458 | 4946 | .415 | 36.71 | .412 |
| Included | 616072 | 164750 | .721 | 38.59 | .263 |

N = 751

[a] Each difference is significant at $p < .001$.

[b] South = Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, N. Carolina, Oklahoma, S. Carolina, Tennessee, Texas, Virginia, and W. Virginia.

While the exclusion of these riots partially undermines Spilerman's conclusions regarding the magnitude of population and region effects, the effects are even more detrimental when assessing diffusion effects. Because smaller riots tend to flow from larger ones, eliminating smaller riots has a tendency to obscure diffusion effects. Furthermore, because contagion controlled by distance may be limited to smaller riots, the effect of spatial heterogeneity would also be obscured, while the effects of severity, Black population size, and region would be artificially inflated. Therefore, the present study defines the population as the group of all 313 cities that experienced at least one riot from 1964-1971.[11]

Another advantage of Carter's data is that he gathered several crucial indicators of riot severity for each incident. These indicators were (1) the number of arrests, (2) the number injured, (3) the number of arsons, (4) the number killed, and (5) the number of days of rioting which were combined to produce a

[11] Potential for bias due to selection exists in this analysis because only cities that experienced at least one riot are included. This potential is unavoidable because it is impossible to determine exactly which of the cities that did not experience a riot had a legitimate risk of experiencing one. To examine the present analysis for such bias, I analyzed the data after including an additional 200 non-riot cities. These cities were all those US cities that had populations of at least 25,000 and Black populations of at least 1,000 and did not experience a riot. Although the coefficient relating the effect of Black population size becomes stronger (because, on the average, non-riot cities had significantly smaller black populations), the remainder of the results show no appreciable differences from those presented in the main body of the paper. Appendix C gives the results of several key models calculated from the expanded data set.

composite severity index (see Appendix B for details).[12] Because media attention and thus infectiousness is likely predicated on severity, such information is important to understanding how riots spread.

Non-White population size for each year and city in the study is calculated by linear interpolation anchored by census data for 1960 and 1970. Non-White population (rather than actual Black population) is used to permit interpolation between 1960 and 1970 values for all cities in the study.[13] The locations of the geographic centers of each city were extracted the Omni Gazetteer of the United States of America, and distances between each pair of cities were calculated using a variant of the "great circle" method (Fitzpatrick and Modlin 1986) which recognizes the curvature of the earth's surface in calculating distances.

**MODEL ESTIMATION**

Models derived and estimated in the present analysis follow the form

$$l_n(t) = \exp[\boldsymbol{\alpha}\mathbf{x}_{it} + \boldsymbol{\beta}\mathbf{c}_{it}] \qquad (12)$$

where $\boldsymbol{\alpha}$ is a vector of parameters indicating the effects of time-varying and time-invariant intrinsic factors ($\mathbf{x}_{it}$) on the hazard of adoption and $\boldsymbol{\beta}$ is a vector of parameters indicating the effects of various contagion variables ($\mathbf{c}_{it}$). These types of models can be straightforwardly estimated using partial-likelihood estimation (Cox, 1972). Cox regression does not require the analyst to specify the form of the baseline hazard, thereby making the maximization procedure dependent only on the estimated values of the hypothesized covariates.[14]

When survival analysis is conducted, the potential effects of unobserved heterogeneity must be carefully considered (Yamaguchi 1991; Allison 1984). A particularly pressing concern for the present analysis is the lack of independence among repeated observations made on the same unit. Because analysis of collective violence demands inclusion of repeated events, and it is unlikely that all sources of intra-unit dependence are accounted for in estimated models, unobserved heterogeneity may introduce a downward bias in standard error estimates. In the present data, 160 cities experienced more than one riot, making the analysis highly susceptible to this problem.

A variety of methods have been suggested to correct for bias introduced by unobserved heterogeneity in survival analysis (Allison 1984; Flinn and Heckman 1982a; 1982b; Heckman and Singer 1982; 1984; Yamaguchi 1986; Tuma 1985; Trussell and Richards 1985). Of these, a number of the more general methods require assumptions either about the distribution of unobserved characteristics or the functional form of the baseline hazard which are not tenable for the present analysis. Therefore, correction for unobserved heterogeneity is introduced in the present study by incorporating a control variable, the number of prior riots which have occurred in a city. Including variables which represent the prior history of the individual unit is a practical procedure that minimizes the effects due to correlation within the same city and does not demand the restrictive assumptions of more general methods (Allison 1984).

---

[12] Although crowd size is the most obvious indicator of riot intensity, it is not employed here because of the high level of missing data and the relative inaccuracy of crowd estimates. The number of arsons is used as a proxy for property damage. (See Carter 1983 for evidence justifying this proxy for this set of riots).

[13] For those cities included in this study, the correlation between Black population and non-White population in 1970 was $r = .98$.

[14] There are a large variety of methods to estimate event history models varying in appropriateness for the current task. Many of the models presented were also estimated using alternative techniques but the differences in results were so small that they do not warrant presentation or further discussion.

## RESULTS

The models presented above find a great deal support when tested against the riot data: Diffusion processes were clearly operating during the riot wave. In order to fully illuminate these diffusion patterns, results are presented below in a step-wise fashion. This level of detail is necessary because of the collinearities among the contagion indicators and the step-wise presentation greatly aids in developing meaningful interpretations of these patterns of collinearity.

### Individual Propensities and Aggregate Patterns

Two variables were used in the current analysis to represent cities' intrinsic propensities to riot. The natural log of the nonwhite population size and a dummy variable indicating if the city was located in the south.[15] Although other intrinsic properties may be related to riot rates, analysis was limited to these two city properties for several reasons, the most important reason of which is the limitations of available data. Unlike prior studies that used subsets of cities for which covariates were available, all cities which experienced riots were included in the present analysis. The unfortunate result is that data on structural variables are not available for many of the cities and thus cannot be examined.

Nevertheless, the loss is not likely to be particularly substantial, particularly with respect to understanding diffusion patterns. First, it should be noted that throughout the many analyses of the 1960s rioting that the size of the non-white population and the south indicator are far and away the most powerful predictors of rioting (Spilerman, 1970a; 1971; 1976; Carter 1986; 1990). In fact, the great challenge in this line of research has been to find any theoretically meaningful variables which contribute improved prediction beyond these two core variables. Simply put, these two variables subsume the effects of almost all structural indicators associated with rioting.

As attention has recently been refocused on racial rioting, however, a number of recent analyses (Olzak and Shanahan 1996; Olzak, Shanahan and McEneaney 1996; Myers 1997) have detected patterns of structural covariates related to ethnic competition theory which contributed to rioting in the 1960s. These studies demonstrate that economic competition processes and residential segregation are related to racial rioting. Furthermore, all three of these studies purport to find theoretically meaningful effects above controls inserted for population and region.

It is important to realize though that the two control variables used in the present study mirror exactly those variables found to be paramount in early studies, while those used in these three recent studies do not. In the two studies conducted by Olzak and colleagues, the population controls used are the log of the population size and the percent Black. However, the population control variable which has been shown to be most relevant to the rioting is the log of the nonwhite population size (See especially Spilerman 1970a; 1976; Carter 1983; 1986). Whether segregation and competition effects Olzak produced would be maintained if the log of the nonwhite population was inserted is an open question. Myers (1997) used the appropriate population control variable, but did not include a region control variable. While this procedure was used to illuminate the effects of structural variables that were masked by the regional dummy, it is unlikely that any of the structural variables would have retained significance had the South dummy been incorporated in the models. Thus, despite unresolved arguments about the theoretical significance of Southern region effects on rioting, the South indicator, coupled with the size of the Black Population, remains an extremely efficient set of summary variables. Other structural variables can produce, at most, marginal improvements in the model's predictive power.

Second, although elimination of structural variables is a substantial loss when attempting to track structural effects, this is much less true when attempting to trace diffusion. The danger of course is that unobserved heterogeneity in structural covariates is collinear with contagion variables leading to model misspecification and an overstatement of diffusion effects. Prior analyses conducted using subsets of cities

---

[15] The definition of the south follows Spilerman (1970). See Table 4.

for which structural covariates are available (Myers 1997) show that the contagion constructs are generally not collinear with structural variables and therefore allow separate analyses of each. Furthermore, the magnitude of the effects of structural variables (other than non-white population size and the south dummy) in previous studies is absolutely pale when compared to the effects of diffusion variables introduced herein. Given the deluge of unsuccessful and weak structural variables examined in studies of rioting, it is unlikely that a structural variable accounting for even a small fraction of the diffusion effects will ever be found.

The current analysis of these intrinsic properties is consistent with previous studies of this wave of rioting: The size of the non-White population and the region dummy variable are powerful predictors of rioting[16] (Model 1 of Table 4).[17] Interpretation of these results has been a matter of some debate, but the consistency of these two variables as predictors of rioting is apparent here as in the past.[18] Thus, the current model reiterates that riot rates are affected by intrinsic city characteristics and further demonstrates the robustness of these particular variables as they remain virtually unchanged throughout the remainder of the analysis.[19]

---

[16] The discussion of effect coefficients in this paper refers mainly to p values calculated using asymptotic standard errors. Although I engage in this practice out of convenience, it should be recognized that a more accurate measure of significance can be obtained using likelihood ratio tests (see Tuma and Hannan 1984). Because the effects reported are very strong, the discussion would not differ substantively if likelihood ratio tests were reported. And because the results are given in a step-wise manner and model chi-square values are reported for each model, likelihood ratio tests can easily be calculated from the information reported.

[17] Non-White population figures for both 1960 and 1970 were introduced in these models. Preliminary analyses showed that 1960 figures predicted rioting better in the early stages of the riot wave and 1970 figures predicted better in the latter stages. Therefore, I used linear interpolation anchored by 1960 and 1970 figures to estimate the non-White population in each year for each city. Neither the 1960 or 1970 figures provided improved prediction over the interpolated values in the models presented herein.

[18] Rather than reiterate these arguments, the interested reader is directed to key works specifically addressing these concerns (Spilerman, 1970; 1971; 1972; 1976; Mazur 1972; Olzak and Shanahan 1996; Myers 1997; Lieske 1978, Carter 1986; 1990).

[19] All models also include the prior rioting history control variable. Models were also calculated without the control variable and, as expected, these models demonstrate that including the control causes a slight attenuation of the effects of other variables.

Table 4: Partial-Likelihood Estimates of the Effects of Intrinsic Properties and Cumulative Riot Counts on the Riot Hazard

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Ln of Non-White Population | .368*** | .364*** | .386*** | .386*** | .391*** |
| | (.026) | (.026) | (.028) | (.028) | (.028) |
| South[a] | -.487*** | -.483*** | -.492*** | -.491*** | -.498*** |
| | (.084) | (.084) | (.085) | (.085) | (.085) |
| Cumulative Riots at *t* (CR) | | -.0001 | .0130*** | .0130*** | .0102*** |
| (Eq. 6) | | (.0002) | (.00081) | (.00081) | (.00084) |
| $CR^2 \times 10^{-3}$ | | | -.0182*** | -.0182*** | -.015*** |
| | | | (.0011) | (.0011) | (.0011) |
| Cumulative Riots within | | | | .0496 | 8.02*** |
| current year (CY) (Eq. 7) | | | | (.13) | (.60) |
| $CY^2 \times 10^{-3}$ | | | | | -7.90*** |
| | | | | | (.57) |
| History of Rioting (Control) | .0345* | .0410* | .0310 | .0313 | .0334 |
| | (.015) | (.018) | (.020) | (.020) | (.020) |
| Model $\chi^2$ (df) | 330.84(3) | 331.20(4) | 672.27(5) | 672.42(6) | 890.58(7) |

* p < .05, ** p < .01, *** p < .001 (two-tailed tests). SEs in parentheses.
[a] South = Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, N. Carolina, Oklahoma, S. Carolina, Tennessee, Texas, Virginia, and W. Virginia.

Given the aggregate pattern of riots displayed in Figure 2, it is no surprise that the hypothesized curvilinear effect of total prior adoptions is demonstrated. Model 2 of Table 4 shows that the linear effect of prior riots on the hazard is not significantly different from zero. However, this pattern changes markedly when curvilinear trends are permitted. Model 3 indicates that both the first- and second-order components are highly significant. Furthermore, the pattern of coefficients follows the predicted pattern: the linear term is positive and the squared term is negative. This pattern of results suggests that depending solely on a linear trend when attempting to identify a diffusion process can produce misleading interpretations of the data.

A plot of the effect of cumulative riot count reveals patterns very similar to that predicted by typical diffusion models. Panel B of Figure 3 plots the effect of the two cumulative riot terms on the hazard of adoption using the coefficients from Model 5. Furthermore, the derivative and integral of the function represented in Panel B are plotted in Panels A and C respectively.[20] The parallel between these

[20] If

$$x = \sum_{a \in \mathbf{A}} q_{a,t-1} \,,$$

then the derivative of the polynomial (Panel C) in the event history context is $d\lambda/dx = [\exp(\beta_1 x + \beta_2 x^2)][\beta_1 + 2\beta_2 x]$. The integral of the polynomial (Panel A) must be estimated numerically.

models and those presented in Figure 1 is obvious and verifies that the aggregate wave of rioting fits a diffusion explanation reasonably well.

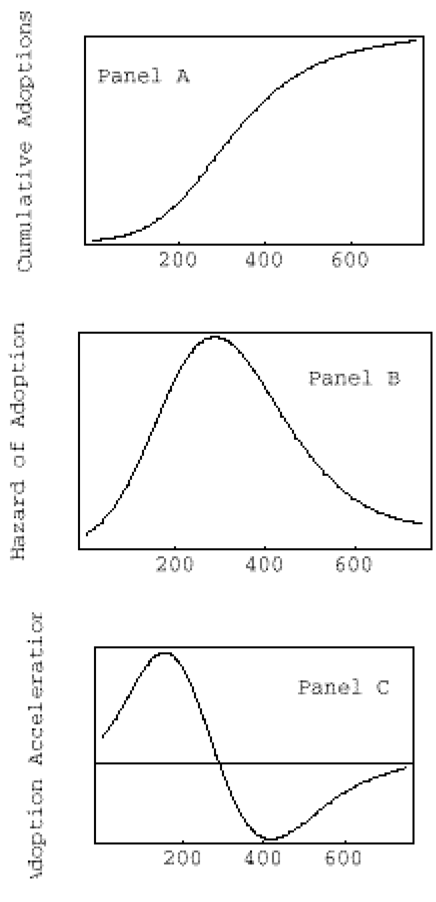


**Figure 3: Estimated Adoption Rates Predicted by Prior Adoptions**

As rioting developed through the 1960s, there were a number of smaller waves within the larger cycle of rioting. Each year, rioting would wax and wane with seasonal changes in weather. This pattern is captured by the curvilinear effect of the cumulative proportion of riots within the current year and is reported in Table 4, Models 4 and 5. The expected pattern of coefficients are the same as those observed for the total cumulative number of riots. Again, the pattern observed is exactly as predicted and the seasonal cycle of rioting is clearly demonstrated.

Although it is tempting to interpret these results as strong evidence that a diffusion process was operating across the riot period, such a conclusion is not necessarily warranted. At best, these results demonstrate that the riot process was consistent with a classical diffusion model. The results do not, however, prove that such a process was operating. In fact, many explanations have been offered to explain the rise and fall of the riots (e.g., McAdam 1982) and any variable which rises and falls over the time period of this study will be collinear with the cumulative riot count. Likewise, any variable which rises and falls on an annual basis (e.g., the temperature) will be collinear with the cumulative annual riot count. Therefore, the method used here is not adequate to adjudicate between these alternative explanations for the rise and fall of the riots either across the entire study period or within each year. It is important, however, to include these effects in the models as controls in order to prevent the clustering that occurs in the overall cycles and in each summer from contaminating the patterns discerned below for the shorter-term influence waves. All caveats aside though, the parsimony of these indicators is noteworthy. As is apparent in Table 4, these very simple variables are powerful predictors of rioting and thus the potential diffusion effects must be taken seriously.

**Temporal Heterogeneity**

Tables 5 and 6 present results testing the short-term contagion variables constructed above. In addition to contagion indicators, each model also contains the set of control variables from the final model

Table 5. Partial-Likelihood Estimates of the Effects of Temporally and Spatially Heterogeneous Contagion on the Riot Hazard

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| *Control Variables* | | | | | |
| Ln of Non-White Population | .394***<br>(.028) | .398***<br>(.028) | .398***<br>(.028) | .402***<br>(.028) | .403***<br>(.028) |
| South | -.492***<br>(.085) | -.488***<br>(.085) | -.488***<br>(.085) | -.489***<br>(.085) | -.486***<br>(.085) |
| Cumulative Riots at *t* (CR) (Eq. 6) | .00904***<br>(.00086) | .00835***<br>(.00087) | .00861***<br>(.00087) | .00830***<br>(.00087) | .00862***<br>(.0017) |
| $CR^2 \times 10^{-3}$ | -.0133***<br>(.0012) | -.0122***<br>(.0012) | -.0125***<br>(.0012) | -.0121***<br>(.0012) | -.0126***<br>(.0012) |
| Cumulative Riots within current year (CY) (Eq. 7) | 7.10***<br>(.62) | 6.82***<br>(.62) | 7.20***<br>(.627) | 6.79***<br>(.617) | 7.21***<br>(.63) |
| $CY^2 \times 10^{-3}$ | -7.00***<br>(.59) | -6.66***<br>(.59) | -7.00***<br>(.59) | -6.63***<br>(.587) | -7.00***<br>(.594) |
| History of Rioting (Control) | .0371<br>(.020) | .0364<br>(.020) | .0348<br>(.020) | .0365<br>(.020) | .0347<br>(.020) |
| *Diffusion Due to Riots in the Previous Week* | | | | | |
| Number of Riots (Eq. 8) | .016***<br>(.0022) | | -.0179***<br>(.0048) | | -.0175***<br>(.0048) |
| Time Decay (Eq. 9) | | .0657***<br>(.0053) | .100***<br>(.010) | | -.0131<br>(.036) |
| Distance Decay (Eq. 10) (Decays over Time) | | | | .0674***<br>(.0052) | .112***<br>(.034) |
| Model $\chi^2$ (df) | 934.64(8) | 1000.86(8) | 1025.64(9) | 1021.89(8) | 1038.99(10) |

* p < .05, ** p < .01, *** p < .001 (two-tailed tests). SEs in parentheses.

of Table 4. These control variables must be included to prevent misinterpretation of contagion result. Absent these controls, positive results for contagion variables could be the result simply of seasonal clustering or clustering during the peak years of rioting. This set of stringent controls lends additional credibility to the contagion patterns detected.

The first three model in Table 5 test for patterns of temporal heterogeneity. Both contagion variables examined in these models have some degree of temporal heterogeneity associated with them. Because contagion is constructed using only those riots which occurred in the past week, even the raw riot count model (Model 1) suggests a simple notion of decay: constant contagion for seven days and none thereafter. The second variable posits a more sophisticated model in which the effect of the riot decays over time. Models 1 and 2 demonstrate that each of the constructions of contagion produces the predicted effect: The greater the amount of contagion experienced by a city, the greater its hazard of rioting. Each effect is highly significant.

Taken at face value, the results of Model 1 mean that no matter where riots occur and no matter when they occur (within the past week), they will increase the likelihood of further rioting. If this effect were sustained, it would mean that the assumption of spatial homogeneity is adequate for the riot process and that only a very simple model of temporal heterogeneity is operating. The hypothesis of national diffusion of rioting through the national mass media would then seem the best explanation of riot diffusion.

The effect of the simple number of riots is not sustained, however. Model 3 of Table 5 examines the first two contagion variables simultaneously and shows that a more sophisticated version of temporal heterogeneity is required. When the effect of riots is permitted to decay over the week that follows its onset, we can see that the time decay model is collinear with the number of riots, completely subsumes the effect of the simpler variable, and is itself highly significant.[21] Riot contagion does appear to decay over time and temporal homogeneity is not supported.

In the analysis that follows, several other hypothesized constructions of contagion are examined. In each case, two versions of each contagion variable were examined parallel to the analysis presented in Table 5: The first version did not decay as a function of time and the second did. In each case, the time-decaying version of the variables subsumed the time-constant version and proved to be a much more powerful construction of contagion, further suggesting the importance of temporal heterogeneity to the collective violence contagion process. To save space and simplify presentation, only the time-decaying version of those variables are presented below.

**Spatial Heterogeneity**

Given that temporal homogeneity is not supported, is there any evidence that undermines its counterpart, spatial homogeneity? In other words, does the distance between adopters and potential adopters matter? The fourth model of Table 5 adds the Riot/City decay variable[22] to the control variables presented in Table 4. As with the previous contagion variable presented, the distance decay model predicts rioting strongly. Nevertheless, the results may be due to the components of the prior variables which are part of the construction of the distance decay variable (the number of riots and time decay). Model 5 re-enters the prior contagion variables so that any significant effect of the distance decay variable can be attributed to distance effects. The coefficient estimated is positive and significant meaning that the less distance between an adopter and a potential adopter, the more influence the prior adoption had on the

---

[21] In fact, the effect of the raw riot count variable becomes significantly negative. When all other contagion variables are entered however, the raw riot count looses almost all of its predictive power through its collinearity with the other contagion variables (see Table 6).

[22] The specifics of the distance decay function is presented in detail in Appendix A.

potential adopter. This finding means that homogenous mixing models are not appropriate for modeling riot diffusion and that some contagion effects are limited in geographic scope.

Table 6: Partial-Likelihood Estimates of the Effects of Riot Severity on Riot Contagion

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| *Control Variables* | | | | | |
| Ln of Non-White Population | .398***<br>(.028) | .399***<br>(.028) | .397***<br>(.028) | .399***<br>(.028) | .398***<br>(.028) |
| South | -.487***<br>(.085) | -.484***<br>(.086) | -.488***<br>(.085) | -.483***<br>(.086) | -.491***<br>(.085) |
| Cumulative Riots at *t* (CR) (Eq. 6) | .00817***<br>(.00087) | .00877***<br>(.00088) | .00861***<br>(.00087) | .00879***<br>(.00088) | .00885***<br>(.00086) |
| $CR^2 \times 10^{-3}$ | -.0118***<br>(.0012) | -.0125***<br>(.0012) | -.0124***<br>(.0012) | -.0125***<br>(.0012) | -.0129***<br>(.0012) |
| Cumulative Riots within current year (CY) (Eq. 7) | 6.64***<br>(.62) | 7.26***<br>(.63) | 7.27***<br>(.63) | 7.18***<br>(.65) | 7.43***<br>(.61) |
| $CY^2 \times 10^{-3}$ | -6.47***<br>(.59) | -6.97***<br>(.60) | -7.01***<br>(.60) | -6.91***<br>(.61) | -7.22***<br>(.58) |
| History of Rioting (Control) | .0366<br>(.020) | .0346<br>(.020) | .0344<br>(.020) | .0346<br>(.020) | .0366<br>(.020) |
| *Diffusion Due to Riots in the Previous Week* | | | | | |
| Number of Riots (Eq. 8) | | -.0116*<br>(.0050) | -.0242***<br>(.0047) | -.0125*<br>(.0048) | |
| Time Decay (Eq. 9) | | -.255***<br>(.048) | | -.251***<br>(.048) | |
| Distance Decay (Eq. 10) (Decays over Time) | | .117***<br>(.036) | | .118***<br>(.036) | |
| Severity (Eq. 11) (Decays over Time) | .097***<br>(.0068) | .297***<br>(.031) | .155***<br>(.012) | .300***<br>(.032) | |
| MLK Riots—April 1968 (dummy) | | | | -.268<br>(.55) | 2.64***<br>(.22) |
| Model $\chi^2$ (df) | 1048.92(8) | 1115.93(11) | 1080.02(9) | 1116.17(12) | 1002.99(8) |

* p < .05, ** p < .01, *** p < .001 (two-tailed tests). SEs in parentheses.

**Riot Severity**

Severity is a powerful engine driving contagion. The finding that riot severity predicts future rioting is one of the most robust in this analysis. The effect of the severity variable is highly significant net of all the controls and other contagion variables included in the analysis (Models 1, 2, and 4 of Table 6). This data supports the theoretical notion that characteristics of individual adoption incidents must be considered in order to adequately understand contagion/diffusion processes.

The puzzling pattern related to riot severity is the change in the coefficient of the time decay variable when severity is added to the model (Model 2). While the time decay variable was positive and highly significant in Table 5, it becomes negative and highly significant when combined with severity. Because much of the contagion effect of very severe riots is controlled when the severity variable is added, the change in the time decay coefficient is most likely generated by the smaller riots. In effect, this means that when severe riots occur, additional small riots can actually slow the rate of adoption. This argument suggests that the contagion effect may be curvilinear: After some maximum amount of rioting, additional rioting makes the process less attractive to other potential rioters. This line of reasoning taps the implicit inclusion of the number of riots in each contagion variable (each contagion variable is summed over all riots), rather than the time decay function, and, if accurate, implies that the simple number of riots in the prior week should be negative when combined in a model with riot severity. Supportive evidence is supplied by Model 3: the effect of the number of riots here is negative and highly significant.

Finally, the exceptional case of April, 1968 is considered. Beginning on April 4, a short wave of rioting broke out in response to the assassination of Martin Luther King, Jr. The extreme number of riots in the one-week period following his death represented a rather marked discontinuity within the riot wave. The extreme clustering of riots from April 4-11 could present a serious problem for a diffusion analysis by accounting for a large portion of the effects of the proposed contagion variables. Therefore, a dummy variable for April 4-11 was added to Model 2 to test for such a possibility. As is apparent in Model 4, the dummy variable has very little effect on the other variables in the analysis and thus is of little concern on that level.

The insignificant effect of the dummy though, is somewhat surprising because it means that net of all the intrinsic and diffusion variables, there was no more rioting from April 4-11 than would be predicted by the other variables in the model. If the diffusion variables were not present, this dummy would be positive and highly significant (Model 5), therefore, the observed effect in Model 4 means that the posited contagion models account well for the pattern of riots, even within this extraordinarily dense series of events.

**DISCUSSION**

This analysis of the racial rioting in the United States establishes that diffusion was one important force driving the pattern of collective violence observed from 1964-1971. Contrary to earlier studies which either found geographic diffusion to be negligible (Spilerman 1970a; 1972) or suggested that the collective violence processes can be modeled as a smooth adoption curve (Pitcher, Hamblin, and Miller 1978), this analysis demonstrates that diffusion occurred both through spatially homogenous and spatially heterogeneous processes and was characterized by a series of waves-within-waves. The combined effects of these diffusion processes were absolutely immense. In fact, these diffusion effects challenge Black population size and the regional indicator as the most important predictors of rioting (compare Model 2 of Table 6 with model presented in Table 4). Furthermore, this study suggests a general approach to studying the diffusion of collective violence characterized by several departures from previous diffusion research. In particular, modeling adoption acts rather than focusing on adopters, allowing adopters to adopt the diffusing behavior more than once, recognizing brief waves of contagion within the larger cycle, and allowing both temporal and spatial heterogeneity were shown to be of substantial importance when modeling inter-actor influence.

In addition to documenting spatial and temporal heterogeneity in contagion influence, this analysis also identified heterogeneity of riot severity as an essential component of the diffusion process. Riots which were relatively more severe had greater infectiousness, propelling much more additional rioting than did smaller riots. This discovery is important because it calls attention to the character of each individual adoption as sources of contagion heterogeneity. Rather than merely the characteristics of the adopter or the behavior being important to diffusion, the traits of the adoption act must also be considered.

While the current analysis convincingly demonstrates that diffusion processes were major contributors to the rioting in the 1960s, important issues regarding the diffusion of collective violence remain. The first of these is the interpretation of the three levels of action waves. The annual waves, waxing in the summers and waning in the winters, seem to be largely controlled by seasonal weather changes, but what of the others? The cumulative count of riots follows a typically sigmoid pattern and suggests that rioting initially gained and then lost, currency as an effective means of protest. Tomlinson (1968) and Spilerman (1970a) suggested that a pervasive "riot ideology" was in place uniformly throughout Black communities and that because of this even distribution of ideology, riot propensity was only a function of the number of people available to riot. While the argument about riot propensity has been critically assessed and rejected, it is equally clear that an ideology supporting rioting as a legitimate form of protest action was present in Black communities in the 1960s.[23] Rather than this ideology being uniformly in place prior to the start of the riot wave however, the current analysis suggests that the acceptance of rioting as an effective protest tactic increased through the first half of the riot wave and then was incrementally abandoned (or its expression suppressed) in the second half. Each micro-wave of rioting increased the acceptance of rioting into 1968 at which point additional riots began to decrease the attractiveness rioting as a profitable tactic.

On the other hand, acceptance of an ideology does not lead to continual action. Particularly in the case of collective violence, expression of ideology through action has major costs associated with it in the form of physical effort, potential acts of repression, risk of injury, and complete breaks with life routines. A greater push than simple acceptance of ideology is necessary. When individuals see other riots happening in which the costs of participation seems relatively low, these models provide additional assurance that rioting is not only a legitimate means of expression, but also that the cost of participation will not be prohibitive. This modeling and rational calculus is thought to be the source of the micro-clusters of rioting which are characterized by the contagion variables investigated in this paper.

Several other issues are suggested by the current analysis. First, there is the issue of exhaustion or ceiling effects which are indicated by several trends in the data such as the negative effect of additional riots beyond very severe ones. The negative effects of many riots suggest that extremely intense or widespread rioting may saturate the population's ability to sustain rioting. In other words, there may be an exhaustion effect driven by short-term negative reactions to rioting, suggesting that a curvilinear time-decay model may provide more accurate prediction. This pattern may be theoretically important because it suggests a mechanism which could explain why the riot wave began to decline.

Second, the analyses presented above demonstrate that national (or spatially homogenous) diffusion can occur simultaneously with regional (or spatially heterogeneous) diffusion. Because spatially homogenous diffusion is dependent upon the technology of mass media, the relative importance of spatially homogenous and heterogeneous diffusion should be expected to vary based on the historical epoch of the collective violence wave in question. Specifically, as one studies collective violence waves in times prior to radio and television, national-level diffusion should be a much weaker force relative to distance-dependent diffusion. For example, in Rudé's (1964; 1972) studies of protest and riots, he documented rebellious activity diffusing along major transportation routes, suggesting that information about collective activity

---

[23] Even the diffusion of seemingly frivolous or fad-like behaviors are often accompanied by some sort of ideological justification. As Aquirre, Quanrantelli, and Mendoza (1988:577) concluded in a study of the diffusion of streaking across college campuses in 1974, "Streaking was widely acknowledged in the press as an act of inter-generational symbolic protest, influenced by the then-new Woodstock sexual morality of the 60s and 70s."

was communicated by travelers along trade route networks. In such a system, temporally homogenous diffusion is implausible and spatial heterogeneity would find much greater support. This issue is particularly important given the on-going evolution of communication technology. As this technology progresses, the relevance of spatial heterogeneity may wane further or change in character reflecting new communication networks.

The final issue brought forward by these data is the effect of repression on diffusion patterns. The very character of collective violence as a form of collective action ensures that some level of repression will be brought to bear on the action. The effects of varying levels of repression may either subdue violence (contributing to exhaustion effects) or propel it as participants rebel against domination. The effects of repression on diffusion, therefore, are a prime target for future development of diffusion models for collective violence and other protest.

**REFERENCES**


Aguirre B. E., E. L. Quarantelli, and Jorge L. Mendoza. 1988. "The Collective Behavior of Fads: The Characteristics, Effects, and Career of Streaking." American Sociological Review 53(4):569-584.

Allison, Paul D. 1984. Event History Analysis: Regression for Longitudinal Event Data. Newbury Park: Sage Publications.

Baron, Robert A. and Victoria M. Ransberger. 1978. "Ambient Temperature and the Occurrence of Collective Violence: The 'Long, Hot Summer' Revisited." Journal of Personality and Social Psychology 36(3):351-360.

Berry, Frances Stokes, and William D. Berry. 1990. "State Lottery Adoptions as Policy Innovations: An Event History Analysis." American Political Science Review 84(June):395-415.

Burt, Ronald S. 1987. "Social Contagion and Innovation: Cohesion versus Structural Equivalence." American Journal of Sociology 92(6):1287-1335.

Carter, Gregg Lee. 1983. Explaining the Severity of the 1960's Black Rioting. Unpublished Dissertation. Columbia University.

Carter, Gregg Lee. 1986. "The 1960s Black Riots Revisited: City Level Explanations of Their Severity." Sociological Inquiry 56(2):210-28.

Carter, Gregg Lee. 1990. "Collective Violence and the Problem of Group Size in Aggregate-Level Studies." Sociological Focus 23(4):287-300.

Carter, Gregg Lee. 1997. "The Intersection between Social Conflict and Collective Definitions of Reality: Why African-American Rioting Ended." In Perspectives on Current Social Problems, ed. Gregg Lee Carter. Boston: Allyn and Bacon.

Casetti, E. and R. K. Semple. 1969. "Concerning the Testing of Spatial Diffusion Hypotheses" Geographical Analysis 1(3):254-9.

Charlesworth, Andrew. 1979. Social Protest in a Rural Society. Cambridge: Institute of British Geographers.

Coleman, James S., Eliho Katz, and Herbert Menzel. 1966. Medical Innovation. Indianapolis: Bobbs-Merrill.

Cox, D. R. 1972. "Regression Models and Life Tables." Journal of the Royal Statistical Society, Series B 34(2):187-202.

Fitzpatrick, Gary L. and Marilyn J. Modlin. 1986. Direct-Line Distances: United States Edition. Metuchen, N.J.: Scarecrow Press.

Fliegel, Frederick C. and Joseph E. Kivlin. 1966. "Attributes of Innovations as Factors in Diffusion." American Journal of Sociology 72(3):235-48.

Flinn, Christopher J. and James J. Heckman. 1982a. "Models for the Analysis of Labor Force Dynamics." In Advances in Econometrics, ed. J. Hildebrand. Cambridge: Cambridge University Press.

Flinn, Christopher J. and James J. Heckman. 1982b. "New Methods for Analyzing Individual Event Histories." Sociological Methodology 11:99-140.

Greve, Henrich R., David Strang, and Nancy Brandon Tuma. 1995. Specification and Estimation of Heterogeneous Diffusion Models. Sociological Methodology 25:377-420.

Griliches, Z. 1957. "Hybrid Corn: An Exploration in the Economics of Technological Change." Econometrica 25(4):501-22.

Hägerstrand, Torsten. 1953. Innovation Diffusion as a Spatial Process. Chicago: University of Chicago Press.

Hamblin, Robert L., R. Brooke Jacobsen, and Jerry L. L. Miller. 1973. A Mathematical Theory of Social Change. New York: John Wiley & Sons.

Heckman, James J. and Burton Singer. 1982. "The Identification Problem in Economic Models for Duration Data." In Advances in Econometrics, ed. J. Hildebrand. Cambridge: Cambridge University Press.

Heckman, James J. and Burton Singer. 1984. "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data." Econometrica 52(2):271-320.

Hedström, Peter. 1994. "Contagious Collectivities: On the Spatial Diffusion of Swedish Trade Unions, 1890-1940." American Journal of Sociology 99(5):1157-79.

Jenkins, J. Craig and Craig M. Eckert. 1986. "Channeling Black Insurgency: Elite Patronage and Professional Social Movement Organizations in the Development of the Black Movement." American Sociological Review 51(6):812-29.

Jiobu, Robert M. 1971. "City Characteristics and Racial Violence." Social Science Quarterly 55(1):52-64.

Kelly, William R. and Larry Isaac. 1984. "The Rise and Fall of Urban Racial Violence in the U.S.: 1948-1979." Research in Social Movements Conflict and Change 7:203-33.

Koopmans, Ruud. 1993. "The Dynamics of Protest Waves: West Germany, 1965 to 1989." American Sociological Review 58(5):637-58.

Le Bon, Gustave. [1895] 1960. The Crowd: A Study of the Popular Mind. New York: Viking Press.

Lieske, Joel A. 1978. "The Conditions of Racial Violence in American Cities: A Developmental Synthesis." The American Political Science Review 72(4):1324-1340.

Mahajan, Vijay and Robert A Peterson. 1985. Models for Innovation Diffusion. Beverly Hills: Sage Publications.

Mazur, Allen. 1972. "The Causes of Black Riots." American Sociological Review 37(4):490-493.

McAdam, Doug. 1982 Political Process and the Development of Black Insurgency, 1930-1970. Chicago: University of Chicago Press.

McElroy, Jerome L. and Larry D. Singell. 1973. "Riot and Nonriot Cities: An Examination of Structural Contours." Urban Affairs Quarterly 8(3):281-302.

McPhail, Clark. 1991. The Myth of the Madding Crowd. New York: DeGruyter.

McPhail, Clark. 1994. "Presidential Address--The Dark Side of Purpose: Individual and Collective Violence in Riots." The Sociological Quarterly 35(1):1-32.

McPhail, Clark and Ronald T. Wohlstein. 1983. "Individual and Collective Behavior within Gatherings, Demonstrations and Riots." Annual Review of Sociology 9:579-600.

Midlarsky, Manus I. 1978. "Analyzing Diffusion and Contagion Effects: The Urban Disorders of the 1960s." American Political Science Review 72(3):996-1008.

Mintrom, Michael. 1997. "Policy Entrepreneurs and the Diffusion of Innovation." American Journal of Political Science 41(July):738-70.

Mooney, Christopher Z. 1997. "Social Learning or Political Threat: Is the Regional Effect on the Diffusion of State Policy Always Positive and Unidirectional?" Presented at the 1997 Annual Meetings of the Southern Political Science Association.

Mooney, Christopher Z. and Mei-Hsien Lee. 1995. "Legislating Morality in the American States: The cases of Pre-Roe Abortion Regulation Reform." American Journal of Political Science 39:599-627.

Morgan, William R. and Terry Nichols Clark. 1973. "The Causes of Racial Disorders: A Grievance-Level Explanation." American Sociological Review 38(5):611-624.

Morris, Aldon D. 1984. The Origins of Civil Rights Movement: Black Communities Organizing for Change. New York: Free press.

Myers, Daniel J. 1997. "Racial Rioting in the 1960s: An Event History Analysis of Local Conditions." American Sociological Review 62(1):94-112.

National Advisory Commission on Civil Disorders. 1968. Report of the National Advisory Commission on Civil Disorders. New York: Bantam Books.

Oberschall, Anthony. 1978. "The Decline of the 1960s Social Movements." Research In Social Movements, Conflict and Change 1:257-89.

Oberschall, Anthony. 1989. "The 1960 Sit-ins: Protest Diffusion and Movement Take-off." Research In Social Movements, Conflict and Change 11:31-53.

Oliver, Pamela E. 1989. "Bringing the Crowd Back In: The Nonorganizational Elements of Social Movements." Research in Social Movements, Conflict and Change 11:1-30.

Olzak, Susan. 1987. "Causes of Ethnic Protest and Conflict in Urban America, 1877-1889." Social Science Research 16(2):185-210.

Olzak, Susan. 1992. The Dynamics of Ethnic Competition and Conflict. Stanford, Stanford University Press.

Olzak, Susan and Suzanne Shanahan. 1996. "Deprivation Race Riots: An Extension of Spilerman's Analysis." Social Forces 74(3):931-961.

Olzak, Susan, Suzanne Shanahan, and Elizabeth H. McEneaney. 1996. "Poverty, Segregation, and Race Riots: 1960 to 1993." American Sociological Review 61(4):590-613.

Pitcher, Brian L., Robert L. Hamblin and Jerry L. L. Miller. 1978. "Diffusion of Collective Violence." American Sociological Review 43(1):23-35.

Rasler, Karen. 1996. "Concessions, Repression, and Political Protest in the Iranian Revolution." American Sociological Review 61(1):132-152.

Rogers, Everett M. 1995. Diffusion of Innovations Fourth Edition. New York: Free Press.

Rogers, Everett M. 1986. The New Media in Society. New York: The Free Press.

Rudé, George. 1964. The Crowd in History: A Study of Popular Disturbances in France and England, 1730-1848. New York: Wiley.

Snyder, David and William R. Kelly. 1977. "Conflict Intensity, Media Sensitivity and the Validity of Newspaper Data. American Sociological Review 42(1):105-123.

Soule, Sarah A. and Yvonne Zylan. 1997. "Runaway Train? The Diffusion of State-Level Reform in ADC/AFDC Eligibility Requirements, 1950-1967." American Journal of Sociology 103(3):733-62.

Spilerman, Seymour. 1970a. "The Causes of Racial Disturbances: A Comparison of Alternative Explanations." American Sociological Review 35(4):627-49

Spilerman, Seymour. 1970b. Governmental Units Analysis Data, 1960: Urban Racial Disorders, 1961-1968 [MRDF]. University of Wisconsin, Data and Program Library Service.

Spilerman, Seymour. 1971. "The Causes of Racial Disturbances: Test of an Explanation." American Sociological Review 36(3):427-42.

Spilerman, Seymour. 1972. "Strategic Considerations in Analyzing the Distribution of Racial Disturbances." American Sociological Review 37(4):493-499.

Spilerman, Seymour. 1976. "Structural Characteristics of Cities and the Severity of Racial Disorders." American Sociological Review 41(5):771-93.

Stark, Margaret J. Abudu, Walter J. Raine, Stephen L. Burbeck, and Keith K. Davison. 1974. "Some Empirical Patterns in a Riot Process." American Sociological Review 39(6):865-876.

Strang, David. 1990. "From Dependency to Sovereignty: An Event History Analysis of Decolonization 1870-1987." American Sociological Review 55(6):846-860.

Strang, David. 1991a. "Adding Social Structure to Diffusion Models: An Event History Framework." Sociological Methods and Research 19(3):324-53.

Strang, David. 1991b. Global Patterns of Decolonization, 1500-1987. International Studies Quarterly 35(4):429-454.

Strang, David. 1995. Mhdiff: User Documentation. Technical Report 95-3, Department of Sociology, Cornell University, Ithaca, New York.

Strang, David and John W. Meyer. 1993. "Institutional Conditions for Diffusion." Theory and Society. 22(4):487-511.

Strang, David and Nancy Brandon Tuma. 1993. "Spatial and Temporal Heterogeneity in Diffusion." American Journal of Sociology 99(3):614-39.

Tarrow, Sidney. 1994. Power in movement. Cambridge: Cambridge University Press.

Tomlinson, T. M. 1968. "The Development of a Riot Ideology among Urban Negroes." American Behavioral Scientist 11(4):27-31.

Trussell, James and Toni Richards. 1985. "Correcting for Unmeasured Heterogeneity in Hazard models Using the Heckman-Singer Procedure." Sociological Methodology 14:242-76.

Tuma, Nancy Brandon. 1985. "Effects of Labor Market Structure on Job-Shift Patterns." In Longitudinal Analysis of Labor Market Data, eds. J. J. Heckman and B. Singer. Cambridge: Cambridge University Press.

Tuma, Nancy Brandon and Michael T. Hannan. 1984. Social Dynamics: Models and Methods. San Diego: Academic Press.

Turner, Ralph H. and Lewis M. Killian. 1972. Collective Behavior. 2nd ed. Englewood Cliffs, NJ: Prentice-Hall.

U.S. Senate Committee on Government Operations. 1968. Staff Study of Major Riots and Civil Disorders: 1965 through July 31, 1968. Washington, D.C.: U.S. Government Printing Office.

Valente, Thomas W. 1995. Network Models of the Diffusion of Innovations. Cresskill, NJ: Hampton Press.

Yamaguchi, Kazuo. 1986. "Alternative Approaches to Unobserved Heterogeneity in the Analysis of Repeatable Events." Sociological Methodology 16:213-49.

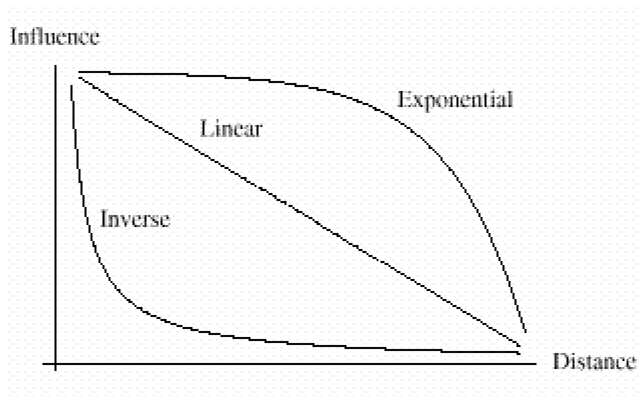
Yamaguchi, Kazuo. 1991. Event History Analysis. Newbury Park: Sage Publications.

## APPENDIX A. DISTANCE DECAY FUNCTIONS

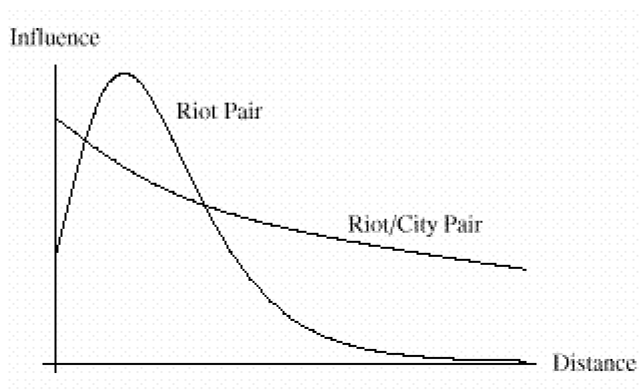
The general notion that contagion effects decay as a function of distance between prior and potential adopters has been used in some prior studies of diffusion (e.g., Strang and Tuma 1993; Hedström 1994) but it is not clear that the specific form of the decay function has been carefully considered. This is important because even if distance-related effects are present in data, they may not be detected or their magnitude may be understated if the hypothesized decay function is inaccurate. Typically, one of two strategies has been adopted when selecting a decay function. The first strategy is apparently arbitrary: Analysts select a fairly simple decay model which seems to produce the desired effect, skirt the issue of adequacy, and move ahead with their analyses which show that the proposed decay function provides a better-than-random fit. In such cases, claims that a distance-related effect exists is usually justified, but the accuracy of the function cannot be determined using such a method.

A second strategy is only marginally more satisfying that the first. Here, authors rely on precedent, using decay functions that have detected distance effects in previous studies. Unfortunately, the precedent functions were usually selected arbitrarily, thus the second strategy is little better than the first. Furthermore, this strategy is blind to the character of the data under scrutiny. One cannot assume that decay functions appropriate for one phenomenon will be useful for another.

When there are no immediately apparent reasons to use any particular decay function, the best strategy is to test several hypothesized functions and locate evidence regarding their relative adequacy. Therefore, the remainder of this appendix discusses and competitively examines five classes of decay functions. The first three of these are models commonly employed in prior research: The linear decay model (which should be viewed as a simplistic baseline model), the exponential decay model representing the set of convex decay models, and the inverse decay model representing the set of convex models. The exponential function has the most precedent in diffusion research, but the inverse function




Common Decay Models




Data Driven Decay Models

**Figure A-1: Hypothesized Distance Decay Models of Infectiousness**

has also proved useful. The final two models are data driven models and are specific to the riot data under examination. One is based on the distribution of riot-pair distances and the other considers both the distribution of riot-pairs and city-pairs. An example of each class of functions is plotted in Figure A-1.

The linear model represents the simple notion that contagion decays over distance at a constant rate. That is, when a contagious event occurs, the difference in contagious influence experienced by two cities 100 and 200 miles from the source is the same as the difference experienced by two cities 400 and 500 miles from the source. The linear model is attractive in its simplicity and is plausible, but alternatives immediately come to mind. Suppose instead, that contagious influence is limited such that it has a profound effect near the contagious event but declines so rapidly that it has virtually no effect two or three hundred miles away. This model suggests a convex curvilinear function which approaches its asymptote of zero fairly quickly. There are many functions which could represent such a model, one of which is the inverse decay model (calculated by 1/distance). Although the model suffers from several problems including severe dependence on the metric of the distance measure and extreme values when distance is very small (culminating in the inevitable divide-by-zero problem), it has been successfully applied in certain contexts (e.g. Hedström 1994; Myers 1997).

The exponential decay model suggests a very different decay process. In the inverse model, contagion is only powerful in locations relatively close to the contagious event; within a relatively short distance, the contagious effect become negligible. The exponential model is, in this respect, the opposite of the inverse model. Instead of decaying quickly near the source and slowly far from the source, the exponential model decays slowly near the source and accelerates as distance increases. This model has been used in a number of network diffusion studies to detect distance-related decay.

All three models are plausible for most diffusion processes, but specific empirical circumstances may require special considerations. For example, analyses presented in the main paper suggest that an exhaustion or ceiling effect exists with respect to riot contagion. Given this empirical pattern, one hypothesis about riot contagion is that while it does decay over distance in a general sense, this effect may be the opposite at very short distances from a riot city. To give a simplified illustration, suppose that when a riot breaks out, it causes increased mobilization of repressive forces for a 200 mile radius. Even if contagion influence was high within the 200 mile radius, the effect would be subdued by the repressive forces. This situation can be made more realistic by positing that mobilization of repressive forces also decays over distance. The result would be a decay curve similar to the riot pair distribution model of Figure A-1 in which the contagion initially increases over distance and then begins to decline. If such a decay pattern did exist, it would help to account for the exhaustion/ceiling effect discussed in the body of the paper.

On the first pass, this exhaustion decay model appears to be plausible. If we assume for present purposes that riots are only contagious for one week, we can tabulate a list of riot pairs in which one could have influenced the other. Calculating the distance between each of riot pair produces a distribution of distances approximated by the white bars in Figure A-2. Within one week of each riot, the distances of follow-up riots follow the general pattern suggested by riot pair distribution model. Riot rates are fairly high near source events, but are even higher about 600 miles away after which they decline to a relatively low level.

The pattern is misleading however. The distribution of distances between contagious riot-pairs must be, in part, a product of the underlying distribution of city-pair distances. In other words, the body of possible city-pair distances defines the underlying random probability of contagious riot-pairs. The empirical plausibility of the riot-pair decay model is eroded when the distribution of city-pairs is examined. In Figure A-2, the gray bars approximate the distribution of all city-pair distances in the riot data set and it

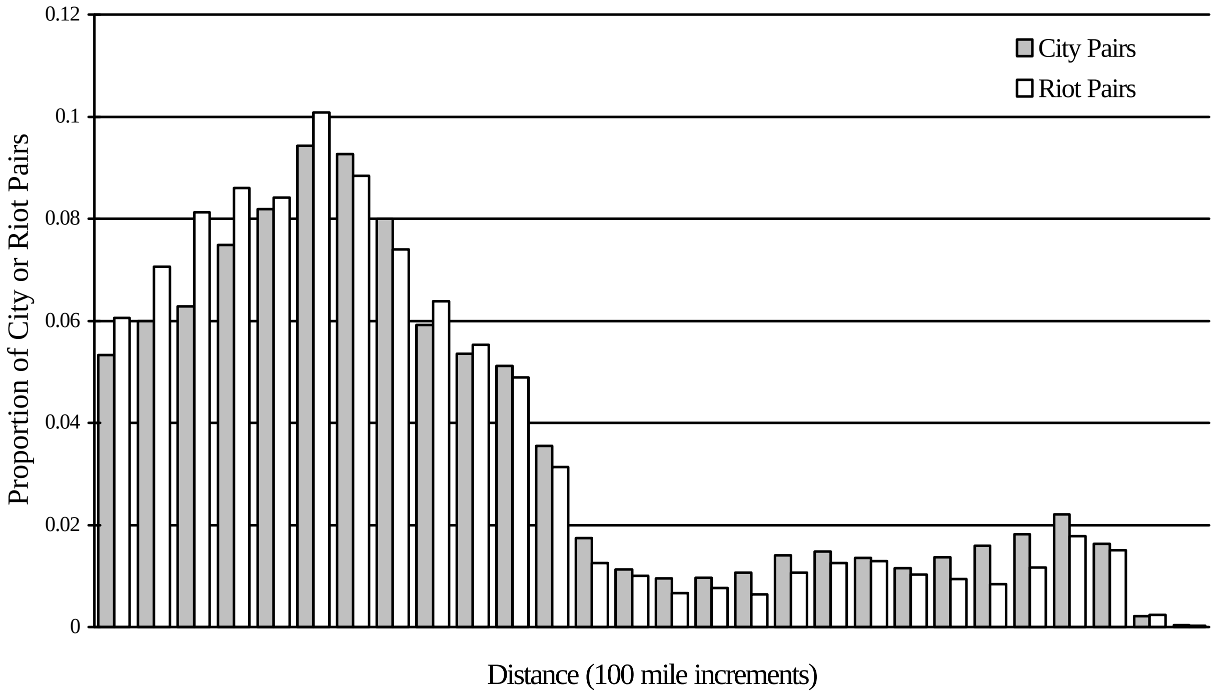



**Figure A-2: Distribution of Riot and City Pair Distances**

is apparent that the distribution is far from uniform.[A1] Furthermore, the parallel between this distribution and the distribution of riot pairs is obvious, apparently undermining the exhaustion decay hypothesis.

Despite the commonalities between the riot-pair distribution and the city-pair distribution, a careful examination of the two distributions reveals that the riot-pair distribution does depart from the city-pair distribution, albeit in different way than suggested by the riot-pair decay model. The difference between these two distributions defines another function which provides yet another reasonable hypothesis about the actual distance decay of riot contagion.

To estimate a decay function which contrasts the riot-pair and city-pair distance distributions, I first estimated the cumulative distribution function for each distribution. Preliminary inspection of both probability distribution functions (approximated in Figure A-2) reveal that the cumulative distribution functions are sigmoid in shape and the inflection points of these distributions approximates that of a Gompertz function.[A2] Therefore, to capture this pattern, I fit the Gompertz function

$$y = a + b \exp\left[-\exp\left(-g\,(x-d)\right)\right] \tag{A1}$$

[A1] Even if cities are distributed uniformly, the distribution of pairs will not be uniform because of a distributional distortion caused when a boundary contains the cities. The maximum distance from cities near the boundary is considerably greater than from those cities located near the center of the region. In the context of the riot data which is bounded by the United States border, this means that while a riot can occur 2000 miles away from cities in California or New York, it is not possible for riots to occur 2000 miles away from cities in Kansas or Missouri. Thus, the distribution of city-pair distances cannot be not uniform.

[A2] Gompertz functions are asymmetric sigmoid functions in which the inflection point occurs at y = 1/*e* ≈ .37.

to each of the data sets (city-pairs and riot-pairs) using non-linear least-squares. The estimated parameters for α, β, γ, and δ provided a very close fit to the data as detailed in Table A-1. The derivative of the two functions defined by these estimated parameters (the probability density functions) represents the distribution of distances for each set of pairs and are the continuous variants of the two distributions in displayed in Figure A-2. These distributions are given by substituting the appropriate parameters in the equation:

$$\frac{dy}{dx} = bg\ \exp\left[gd - \exp\left(g\,(d - x)\right) - dx\right]. \qquad \text{(A2)}$$

Table A-1: Gompertz Model Parameters Estimates

| | Distances between City Pairs | Distances between Riot Pairs |
|---|---|---|
| *a* | -.0137 | -0221 |
| | (.00033) | (.0082) |
| *b* | .957 | .980 |
| | (.00041) | (.0010) |
| *g* | .00252 | .00265 |
| | $(1.63 \times 10^{-6})$ | $(3.84 \times 10^{-6})$ |
| *d* | 494 | 442 |
| | (.28) | (.64) |
| $R^2$ | .997 | .999 |

SEs in parentheses.

Comparing the two functions simply requires calculating the ratio of the riot distance *pdf* to the city distance *pdf* to determine the relative probability of a riot occurring at each distance. The resulting function is:

$$I = .998\ e^{\left[\frac{-3.2}{e^{.00265x}} + \frac{3.48}{e^{.00252x}} - .000128x\right]} \qquad \text{(A3)}$$

where I is the infectiousness ratio and x is the distance. This function is plotted in Figure A-1 as the Riot/City Pair distribution model. The plot reveals that the proposed decay function belongs to the concave family of which the inverse function is also a member. However, the Riot/City distribution function is superior to the inverse model because it defeats the aforementioned difficulties of the inverse decay model.

Given this analysis, it appears that the linear and particularly the exponential decay models are inadequate representations of the decay process. Further, the notion behind the riot pairs model is discredited by examining the riot-pair distribution within the context of the city-pair distribution. To verify these observations, I subjected all five functions to a competitive multivariate test. Congruent with the preliminary observations, the exponential and linear models were found to be completely inadequate. Therefore, to simplify the presentation, I present only the multivariate tests of the latter three models for which partial-likelihood models were calculated following the method described in the main paper. In addition to the contagion decay variables, the set of control variables discussed above (see Table 4, Model 5) were also entered in each model. The coefficients associated with these seven control variables were stable and consistent with those coefficients reported in Model 5 of Table 4, therefore, the presentation of these results is simplified by reporting only the coefficients associated with the contagion variables.

The results of six models are reported in Table A-2. The first three models enter each decay function with the set of control variables and these models demonstrate that each decay model is itself a powerful predictor of rioting.[A3] The remaining three models competitively test the decay functions and the results are clear: the decay function derived from the combinations of the riot-pair and city-pair distributions is much more accurate than either the inverse decay function or the riot-pair decay function. In fact, the riot/city distribution function completely subsumes the inverse decay function (Model 4) and the Riot-Pair decay function (Model 5), as well as the combination of the two (Model 6). The effect of the riot/city decay function is still powerful in Model 6 despite obvious collinearities among the decay functions.

Table A-2: Partial Likelihood Tests of Distance Decay Functions

| Distance Decay Model | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| Inverse Decay | 2.40*** | | | .800 | | .806 |
| | (.37) | | | (.50) | | (.51) |
| Riot-Pair Decay | | 90.1*** | | | 10.1 | 10.6 |
| | | (7.6) | | | (17) | (18) |
| Adjusted for City-Pair | | | .0674*** | .0636*** | .0607*** | .0567*** |
| Distribution | | | (.0052) | (.0057) | (.013) | (.013) |

** $p < .01$, *** $p < .001$ (two-tailed tests). SEs in parentheses.
Note: Parameter Estimates for control variables in each model not shown.

In conclusion, it is apparent that the distance decay function derived from the distributions of relevant riot pairs and city pairs provides a superior representation of the pattern of contagion decay in the riot data. Not only is the function more accurate than functions previously used in contagion analyses, it is also grounded empirically and recognizes the spatial distribution among the actors in this particular social system. Given the results presented in this appendix, only the city/riot pair decay model is carried through the analysis in the main paper. The superior performance of the function recommends this method of derivation for future analyses of spatially heterogeneous diffusion processes.

[A3] Each distance decay function was also weighted by the inverse time decay model described previously. Consistent with the findings in the main paper, distance decay variables weighted by time decay consistently out-performed their unweighted counterparts and therefore results from only the weighted versions are presented here. It is also possible to approach the time decay function in a way parallel to the current discussion of distance decay. Such an analysis reveals that the inverse decay model is a highly appropriate representation of temporal decay in the present empirical context.

## APPENDIX B. COMPUTATION OF RIOT SEVERITY

To construct a singular index of severity, I closely followed the method suggested by Carter (1983; 1986). Because the current analysis is focused on the event-level however, I calculated severity for each individual riot rather than aggregating across all riots within a single city. For each indicator of severity, the raw numbers were log-transformed (*ln*[raw + 1], except the duration in days: *ln*[raw]). Using these values, the data were subjected to a principle axis factor analysis with iterations. Only one factor was identified and all severity indicators loaded strongly on this factor (See Table B-1). Using the factor scores produced by the factor analysis, the logged-transformed raw scores for each set of severity indicators were weighted by the appropriate factor score and summed across the five indicators to produce the severity index. This index is highly correlated with each of the individual severity indicators (mean correlation = .745; see Table B-2), and surpasses each as an indicator of severity by incorporating information from all of the other indicators. Furthermore, this method has been shown to produce severity scores highly correlated with previously developed severity indicators (see Carter 1983 for details).

Table B-1: Factor Analysis Results for Severity Indicators

| | Factor Loading | Factor Scores |
|---|---|---|
| Number Injured | .714 | .233 |
| Number Arrested | .786 | .311 |
| Number Killed | .571 | .122 |
| Riot Duration | .689 | .177 |
| Number of Arsons | .777 | .317 |

Table B-2: Correlation Matrix for Severity Indicators

| | Arrested | Arson | Duration | Injured | Killed | Severity |
|---|---|---|---|---|---|---|
| Arrested | ---- | | | | | |
| Arson | .582 | ---- | | | | |
| Duration | .549 | .621 | ---- | | | |
| Injured | .610 | .476 | .458 | ---- | | |
| Killed | .417 | .479 | .307 | .487 | ---- | |
| Severity | .861 | .834 | .704 | .768 | .556 | ---- |

N = 751

# APPENDIX C. RIOT CONTAGION ANALYSIS USING EXPANDED SAMPLE OF CITIES

Table C-1: Riot Contagion Analysis using Expanded Sample of Cities

| | Model 1 (Compare to Model 1 of Table 4) | Model 2 (Compare to Model 5 of Table 4) | Model 3 (Compare to Model 2 of Table 6) | Model 4 (Compare to Model 4 of Table 6) |
|---|---|---|---|---|
| *Control Variables* | | | | |
| Ln of Non-White Population | .446*** (.026) | .472*** (.028) | .478*** (.028) | .477*** (.028) |
| South | -.488*** (.083) | -.496*** (.084) | -.474*** (.084) | -.473*** (.084) |
| Cumulative Riots at *t* (CR) (Eq. 6) | | .0111*** (.00085) | .00965*** (.00089) | .00967*** (.00089) |
| $CR^2 \times 10^{-3}$ | | -.0155*** (.0012) | -.0129*** (.0012) | -.0129*** (.0012) |
| Cumulative Riots within current year (CY) (Eq. 7) | | 7.99*** (.60) | 7.26*** (.64) | 7.17*** (.65) |
| $CY^2 \times 10^{-3}$ | | -7.86*** (.57) | -7.00*** (.60) | -6.88*** (.61) |
| History of Rioting (Control) | .0388** (.014) | -.00035 (.020) | .00279 (.020) | .00285 (.020) |
| *Diffusion Due to Riots in the Previous Week* | | | | |
| Number of Riots (Eq. 8) | | | -.0116* (.0050) | -.0128* (.0054) |
| Time Decay (Eq. 9) | | | -.309*** (.050) | -.304*** (.050) |
| Distance Decay (Decays over Time) | | | .164*** (.038) | .165*** (.038) |
| Severity (Eq. 11) (Decays over Time) | | | .308*** (.032) | .312*** (.032) |
| MLK Riots—April 1968 (dummy) | | | | -.360 (.56) |
| Model $\chi^2$ (df) | 464.22(3) | 1028.34(7) | 1273.16(11) | 1273.58(12) |

* p < .05, ** p < .01, *** p < .001 (two-tailed tests). SEs in parentheses.