MEASURING EVENT DIFFUSION MOMENTUM (EDM): APPLICATIONS IN SOCIAL MOVEMENT RESEARCH[1]

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ABSTRACT

Measuring the diffusion of protests, or more generally, the diffusion of events, is an ongoing task in social sciences. This paper proposes an inter-event approach to study what types of protests tend to diffuse or decline. We develop a standardized, five-step procedure to measure what we define as "event diffusion momentum" (EDM): (1) employ event-based data containing information on the time, location, and features of each protest; (2) define the temporal and spatial ranges of interest; (3) for each observation, count the number of events before and after it within the defined ranges; (4) predict the numbers of post-event and pre-event protests with appropriate count models; (5) calculate the ratios of predicted values for each predictor and confidence intervals using the delta method. The ratio is the EDM. Applying this method to Dynamics of Collective Action (DoCA) data, we identify several micro- and macro-level factors associated with protest diffusion in the United States, 1960–1995. We conclude with the implications and generalizability of the proposed method.

Keywords: Diffusion studies; event diffusion momentum (EDM); social movements; delta method; political process theory; count models

INTRODUCTION

Studying the diffusion of social facts and events is an important task for scholars (Katz, 1999; Moseley, 2004), and topics of study have included pandemics (Jin et al., 2020), crimes (Zeoli et al., 2014), innovations (Dearing & Cox, 2018), organizations (Park, 2006), institutions (Brinks & Coppedge, 2006), and policies

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(Vasi & Strang, 2009). Despite the wide-ranging interest in the topic (or perhaps because of it), scholars have not reached agreement on either the definition of diffusion or its standardized measurement. Protest diffusion is a case in point. Previous works have focused on the social environment and mechanisms of protest diffusion, establishing such explanations as structural grievances (Zhao, 2004), demographic availability (Andrews & Biggs, 2006), institutional and cultural conditions (Brinks & Coppedge, 2006), resources and political opportunities (Zhang, 2016), social networks (Hedström et al., 2000; Myers, 2000), social movement organizations (SMOs), repression and policing (Steinert-Threlkeld et al., 2022), and social media (Brym et al., 2014; Suh et al., 2017). Studies have also considered protest diffusion's social consequences (Biggs & Andrews, 2015; Earl, 2010) and the contents being diffused, such as strategies, tactics, and repertoire (Givan et al., 2010).

Despite the rich findings, there are two main gaps in the literature on protest diffusion. First, the inter-event dynamics deriving from the effects of certain protest features are unclear. For instance, though symbolic protests are widely considered to have signaling effect to trigger more protests (Goldstone, 2004), we have not established a way to assess such effects quantitatively. Scholars are equally unable to identify protests which exhaust political opportunities or resources and prohibit further mobilization (Myers, 2010). Second, the field of protest diffusion requires methodological improvements. Models designed for cumulative diffusion, such as innovations and institutions which endure (Dearing & Cox, 2018; Strang, 1991; Vasi & Strang, 2009), are not suitable for studying protest diffusion which comes and goes. This demands a method integrating the analysis of mobilization and demobilization. Third, terms in the field are open to debate, and their operationalizations are often ad hoc (Della Porta & Tarrow, 2012; Earl, 2010; Jansen et al., 2016; Strang & Soule, 1998). In other words, the field needs to develop a standardized methodological practice, ideally independent of the researcher's assumptions.

In this chapter, we pay attention to the inter-event dynamics of protest diffusion. Borrowing wisdom from epidemiology, we view all protests as potentially contagious and see how certain features of a protest relate to its contagiousness. We measure a term that we coin event diffusion momentum (EDM). We do so by calculating the quotients of the numbers of protests occurring before and after any given event within a symmetrical time window. We define protest diffusion as more subsequent protests (or post-event ones) than preceding protests (or pre-event ones), where EDM > 1. The opposite, protest decay or decline, is defined as fewer subsequent protests than preceding ones, where EDM < 1. Thus, we can identify risk factors at both macro and micro levels related to diffusion or decay, much like how COVID-19 researchers identify different viruses' and patients' contagiousness with indicators like the basic reproductive rate (R0) (Jin et al., 2020).

Our proposed method has the following merits. First, it relies on minimal assumptions and only employs objective measures (e.g., time/location, number of protests within given ranges), thus precluding subjective bias. Second, the EDM value is easy to interpret; we can simply tell whether a protest is diffusive or self-limiting by comparing its EDM to 1. Therefore, EDM helps to explain both mobilization and demobilization. Third, our method excludes the impacts of autocorrelation and time-varying factors; thus, EDMs are comparable across contexts. Fourth and finally, our method converts the study of diffusion into a conventional multivariate approach, thereby allowing us to assess multiple effects at different levels simultaneously.

We begin by reviewing the extant works on diffusion and social movements and their implications for our research. We then discuss the need for methodological innovation in the field. We propose our five-step method and explain our application of it to the Dynamics of Collective Action (DoCA) data from the United States, 1960–1995. We introduce three studies to exemplify the use of our method: (1) an analysis of the features of protest and their relationship with diffusion; (2) an analysis of the effects of US Presidents' and Governors' party affiliations on protest diffusion; (3) an analysis of US Governors' party affiliations and policing. After presenting the results, we conclude with our paper's contributions and implications: we argue that our definition and measurement of protest diffusion can be generalized and applied to diffusion studies in general.

DIFFUSION STUDIES: PUBLIC HEALTH AND SOCIAL SCIENCE PERSPECTIVES

Researchers in epidemiology and public health work to uncover the spatial and temporal diffusion mechanisms of diseases. Along with urbanization and globalization, the increasingly intensive flows of goods and people call for heightened attention to contagious diseases (Neiderud, 2015). The COVID-19 pandemic emphasized the need for this type of research (Jin et al., 2020). In addition to diseases, public health researchers care about the diffusion of other health-related issues like addictions and preventative methods (Moseley, 2004). The analytical perspectives emerging from these efforts serve different research interests and data types. Some focus on "what" diffuses; the content of diffusion could be germs, viruses, or parasites. Others focus on "where" diffusion occurs, such as the media, environment, and contexts that impede or accelerate diffusion (Neiderud, 2015). Still others look at vulnerable populations to see "who" is susceptible to contagion (Chapman & Hill, 2012).

Diffusion is not limited to contagious diseases; it also applies to social contagion. Scholars have noticed the diffusion of innovations (Dearing & Cox, 2018), policies (Biggs & Andrews, 2015), institutions (Brinks & Coppedge, 2006), and norms (Park, 2006). These insights inspired scholars to apply public health methods to social science research on diffusion. For example, in criminology, scholars began to view crimes as related and potentially contagious (Holden, 1986). More recently, by applying the latest statistical tools and GIS methods, criminologists have better understood the spatial and temporal diffusion of crimes, including which types of crimes are more diffusive or contagious (Zeoli et al., 2014).

Unlike work in epidemiology and criminology, social movement studies have paid more attention to the social environment of diffusion and related mechanisms. Yet we could benefit from examining protest features and their relations to diffusion, just as epidemiologists identify contagious patients based on the presence of certain symptoms (Jin et al., 2020). For example, criminology has reported some inspiring findings on copycat crimes (Holden, 1986; Surette, 2014). By the same token, spin-off protests could be inspired or encouraged by a previous protest (McAdam, 2013). Another criminological theory, the "broken windows theory," suggests crimes may signal a "crime-friendly" environment (Gau et al., 2014). Similarly, protests could signal a "movement-friendly" environment and encourage more protests (Zhang, 2016). Given these parallels, we believe turning to the inter-event approach and focusing on protest features may help us understand what kinds of protests tend to associate with the rises and falls in a cycle of protests.

EXPLANATIONS OF PROTEST DIFFUSION

Diffusion can be defined as the expansion of events in number, scale, time, and space. Alternatively, it can refer to latecomers' adoption of previous actions, practices, tactics, and strategies (Katz, 1999). More specifically, social movement scholars have defined protest diffusion in the following senses: a scale shift, namely an increase (or decrease) of protests and participants (Tarrow, 2010); follow-up or spin-off protests directly or indirectly inspired by previous actions (Goldstone, 2004); the spread of emotions, such as anger and grievances triggered by a previous protest and shared by latecomers (Goodwin et al., 2000); social learning and the adoption of prior practices, including repertoire, tactics, and framings (Meyer & Whittier, 1994; Soule, 2004); the growth of networks, organizations, and personnel encouraged by existing actions and organizations (Myers, 2010; Strang & Soule, 1998; Wang & Soule, 2012). According to Givan et al. (2010), we can largely categorize the foci of protest diffusion research as the following: the environment of diffusion ("where"); the mechanisms of diffusion ("how"); the contents of diffusion ("what"); and the impacts of diffusion ("who" and "what").

This chapter is concerned with the "scale shift" aspect of protest diffusion, namely, the rise and fall in the numbers of protests (Tarrow, 2010). Therefore, in our review of the literature, we focus on work that tries to answer the "where" and "how" questions. For the question of "where" diffusion takes place, social movement scholars have mainly studied environmental features, including structural grievances and mass frustration (Zhao, 2004), demographic availability of potential protesters (Andrews & Biggs, 2006), political opportunities (Tilly & Tarrow, 2015), and resources for mobilization (Tarrow, 2011). These variables are at the macro or meso levels, often tapping features of a country (e.g., GDP growth rate, regime change), a state (e.g., unemployment rate), or a city (e.g., density of population/students/universities). These explanations help us understand when and where social movements emerge, yet they are less relevant when our concern is at the level of actors and events.

For the question of "how" diffusion takes place, social movement researchers have closely examined meso and micro-level phenomena, such as the roles of SMOs (Andrews & Biggs, 2006), networks (Hedström et al., 2000), news media (Myers, 2000), Internet and social media (Brym et al., 2014). By integrating temporal and spatial perspectives into their interpretations, they allow more dynamic explanations of not only the emergence but also the demobilization of social movements. The agency of individuals and organizations in social learning, adopting, and strategizing is also appreciated by work in this vein (Jansen et al., 2016). For example, many scholars have noticed how previous success signals opportunities and encourages subsequent protests (Wang & Soule, 2012), something termed "demonstration effects" (Minkoff, 1997; Tarrow, 2011). Overall, this line of research has deepened our understanding of the agentic roles played by SMOs and protest leaders in perceiving signals and seizing opportunities. However, the protest features and inter-protest dynamics in diffusion remain under-studied.

Protest diffusion studies have been influenced by innovation theories, and authors tend to view protest diffusion as comprising the adoption of previous practices (Soule, 2004; Strang, 1991). In terms of methodological practice, researchers have used innovation diffusion models, survival models, and event history analysis (EHA). These techniques are suitable for explaining the expansion of social movements from early risers to followers or the enduring impacts of protests such as desegregation (Biggs & Andrews, 2015). However, they are only applicable to certain types of diffusion: the subjects are all susceptible to diffusion or contagion (e.g., an SMO to a new tactic, a city to a desegregation policy, or a state to the legalization of same-sex marriage). Moreover, the outcomes are binary ("occurred/adopted" vs. "not yet"), and the diffusion process is theorized as cumulative, such as Biggs' (2005) metaphor of protests as wildfire. These methods are often applied to places (Braun & Koopmans, 2010), such as cities, states, or countries as analytical units, analyzing how they are "infected" by or "immune" to diffusion (e.g., desegregation; legalization of euthanasia). While all these methods yield valuable results, when it comes to the characteristics of protests and how they affect diffusion, they are less helpful.

TOWARD AN INTER-EVENT APPROACH

What do we expect in a new methodological tool for studying protest diffusion? First of all, we believe event-level analysis should be the primary focus. Scholars have invented terms describing inter-event dynamics, such as McAdam's (2013) discussion of initiator, spin-off, and spillover movements. Tilly and Tarrow (2015) use the term "scale shift" to refer not only to diffusion but also to the substantial change in the level of mobilization and impact of social movements during a cycle of protests. These terms tap the varying degrees of social movement liveliness and how they change over time. Although these perspectives give us hints about "inter-protest" dynamics, they do not explain what types of protests tend to diffuse or demobilize. These unsolved problems matter in the real world: protests are not simply the products of their environment (Schneiberg & Lounsbury, 2017). Rather, they can change the context and affect subsequent protests. A better understanding of inter-event dynamics could help us to understand the social environment.

Second, the new method should be able to investigate both the mobilization and the demobilization of social movements. Different from technological diffusion which usually lasts, protest diffusion comes and goes. Therefore, the analytical framework should capture the rises and falls in cycles of protests, rather than just focusing on the cumulative process. As Andrews and Biggs (2006) point out, protests and news diffuse within given periods and geographical distances, and the diffusive effects diminish over time and space. Similarly, Tilly and Tarrow write:

> Most mobilization processes eventually reverse themselves... . .We see a number of mechanisms and processes that led to demobilization: Competition among different sources of support; Defection; Disillusionment, as others, both leaders and followers – became embittered by their experience with collective action; repression; institutionalization. (2015, pp. 97–98)

Our proposed method should be able to identify risk factors related to demobilization and thus capture the starting points and ends of protest cycles.

Third, it is ideal for researchers to have minimal assumptions and operationalize with objective measures only. In many approaches, measurements of key variables are subjective, and the results are sensitive to researchers' theorization and operationalization. Common examples include the notions of "centrality," "opportunity," and "ties"; results and conclusions largely depend on how researchers define and measure these notions. For example, as Goodwin and Jasper (1999) pointed out, when researchers define all favorable conditions for protests as "opportunity" or "resources" and establish seemingly plausible post-hoc explanations, the conclusion may suffer from confirmation bias. Furthermore, researchers have not yet reached methodological agreement, and most methods are case-specific, which is not generalizable. Inspired by Minkoff's (1997) notion of "sequencing of social movements," we seek to identify the protests that are followed by an increasing number of subsequent protests or followed by a declining trend. We call this varying degree of contagion event diffusion momentum (EDM). Our goal is to build a generalized multivariate method to identify risk factors associated with diffusion (EDM > 1) or decay (EDM < 1). The next section proposes a standard procedure to calculate EDM using event-based records. We then apply it in three studies to illustrate the use of this method.

PROPOSED METHOD FOR ESTIMATING EDM

We propose a five-step procedure to estimate EDM and its confidence intervals. First, we select data that treat events as observations; the data should record key variables such as time and location of protests. Second, we determine the temporal and spatial ranges of interest; the temporal ranges (t) should be symmetrical around the focal observation. Third, we count the number of pre-event and post-event cases within the defined temporal and spatial ranges for each case. Fourth, after obtaining the counts ($N_{\text{post-}t}$ & $N_{\text{pre-}t}$) for post- and pre-event cases, we employ proper count models to predict event occurrences ($P_{\text{post-}t}$ to $P_{\text{pre-}t}$). Finally, we calculate the ratios (quotients) of the predicted values; these are the EDMs (EDM = $P_{\text{post-}t}/P_{\text{pre-}t}$). The confidence intervals of EDM can be generated using the delta method. A brief version of this five-step method is given in Table 1. We explain it in further detail next.

Step 1: Select Event-Based Data

When studying diffusion, epidemiologists usually pay attention to patients or infections as cases; criminologists usually treat crimes as cases. Similarly, our proposed approach treats events (protests) as observations. Datasets that record events, together with their main features, such as time and location of occurrence, size (number of participants), the involvement of social movement organizations, and the forms of action, violence, and policing, suit our research purpose. In the field of social movement studies, researchers have tracked protests, wars, and other conflicts as observations, creating datasets like the Armed Conflict Location and Event Data (ACLED), the UCDP/PRIO Armed Conflict Dataset, the Dynamics of Collective Action data (DoCA), and so on. Today's scholars can produce high-quality protest event data in an automated manner from various sources using techniques like neural networks (Hanna, 2017; Zhang & Pan, 2019). We select a widely-used dataset in social movement studies, the DoCA dataset, to illustrate our method. The DoCA dataset tracks cases within the United States and has detailed temporal-spatial records for each case. It contains more than 23,000 cases over a long period (1960–1995), thus permitting reliable estimations.

Table 1. A Five-Step Method to Calculate Event Diffusion Momentum (EDM).

Procedure	Values
Step 1: Use an event-based dataset and treat each event i as a focal case.	Case i
Step 2: Set temporal and spatial ranges of interest.	Define spatial and temporal ranges (t) for the present study
Step 3: For any case i, count the number of pre/post-event protests within the given ranges.	$N_{\text{pre-}t}$; $N_{\text{post-}t}$
Step 4: Fit appropriate count models and get predicted values for each predictor.	$P_{\text{pre-}t}$; $P_{\text{post-}t}$
Step 5: Calculate the ratios as the EDMs and their confidence intervals.	$\text{EDM}_t = P_{\text{post-}t}/P_{\text{pre-}t}$ *(CI formula see in-text discussion)*

Step 2: Set Temporal and Spatial Ranges of Interest

In this step, we set the most appropriate temporal and spatial ranges for calculation based on the research scope. After determining the ranges of interest, we count the numbers of pre-event and post-event cases within those ranges for any observation. For the temporal aspect, we use $t = 1, 3, 7, 14, 30, 45, 60$, and 90 days.[2] These allow us to identify both the immediate and the long-term dynamics of protest diffusion. For the spatial ranges, we use state borders instead of geographical distances.

Although the data provide information on location, thus permitting the calculation of distances, we prefer to use state borders to measure social distance or social space for the following reasons. First, states differ in size and population density; using geographical distances may yield misleading conclusions, especially when our primary concern is social mechanisms. Second, social movement diffusion depends less on geographical distances and more on social spaces and networks. When protests are within a single state, we have reason to believe they will share political contexts, behave similarly, and influence each other. For example, student activists in San Diego may respond to an earlier protest at UC Berkeley but not necessarily react to a protest in Phoenix, Arizona, even though the latter's location is much closer.

Step 3: Count the Number of Pre/Post-event Protests

The next step is simple: we count the pre-event and post-event protests for any focal case i within the defined temporal range (t) within the same state. The numbers can be noted as $N_{\text{pre-}t}$ and $N_{\text{post-}t}$. For instance, the number of protests after the focal case in the same state and within 30 days can be noted as $N_{\text{post-30}}$. Thus, social movement diffusion can be identified when the number of subsequent protests is larger than that of preceding protests, or $N_{\text{pre-}t} < N_{\text{post-}t}$. By the same token, social movement decline is defined as $N_{\text{pre-}t} > N_{\text{post-}t}$, and the protests can be seen as self-limiting and discouraging further mobilization.

Step 4: Fit Appropriate Count Models and Get Predicted Counts for Each Risk Factor

After $N_{\text{pre-}t}$ and $N_{\text{post-}t}$ are available, we use them as the dependent variables. Then we fit appropriate count models to estimate the coefficients for each risk factor. Depending on the distribution of the outcome variables, we might opt for Poisson models, zero-inflated models, negative binomial models, and so on; statistical tests are required to choose the right model (Perumean-Chaneya et al., 2013). Based on the models, we can predict each risk factor's fitted values—when all other factors are controlled for and set to typical values, we can determine how many protests happen after/before a certain protest. Following previous practices, the predicted values are noted as $P_{\text{pre-}t}$ and $P_{\text{post-}t}$.

Step 5: Calculate EDM and Confidence Intervals

EDM is defined as the ratio of the predicted counts[3] ($P_{\text{post-}t}$ and $P_{\text{pre-}t}$, respectively) obtained from the model specified in Step 4. The theoretical range for EDM starts at 0 and goes to positive infinity. Most values are expected to distribute around 1, which stands for no significant diffusion. We call it "diffusing," "diffusive," or "expanding" when the EDM is greater than 1; we call it "declining," "decaying," or "self-limiting" when the EDM is lower than 1.

The advantage of using ratios ($P_{\text{post-}t}/P_{\text{pre-}t}$) instead of simply using differences ($P_{\text{post-}t}-P_{\text{pre-}t}$) is that this method can exclude the influence of autocorrelation or any time-varying difference in the social context. For instance, we know the 1960s were relatively active years in the social movement history of the United States. In the 1980s and afterward, the total number of protests declined (see frequencies by "decade" in Table 2). Thus, differences in post-event and pre-event observations will differ across the decades; however, ratios between the two numbers will not be affected. EDMs are comparable, as they are independent of political and historical contexts, thus opening the door to comparative research on protest diffusion.

The next step is to calculate the confidence intervals for the EDMs. The corresponding variance can be approximated using the delta method (Xu & Long, 2005). For example, we have

$$E(EDM_t) \approx \frac{\widehat{P}_{\text{post}_t}}{\widehat{P}_{\text{pre}_t}}$$

and

$$\begin{aligned}\text{var}(EDM_t) &\approx \frac{1}{\widehat{P}^2_{\text{pre}_t}}\text{var}\left(\widehat{P}_{\text{post}_t}\right) + \frac{\widehat{P}^2_{\text{post}_t}}{\widehat{P}^4_{\text{pre}_t}}\text{var}\left(\widehat{P}_{\text{post}_t}\right) - \frac{\widehat{P}_{\text{post}_t}}{\widehat{P}^3_{\text{pre}_t}}\text{cov}\left(\widehat{P}_{\text{post}_t}, \widehat{P}_{\text{pre}_t}\right) \\ &= \left(\frac{\widehat{P}_{\text{post}_t}}{\widehat{P}_{\text{pre}_t}}\right)^2 \left(\frac{\text{var}\left(\widehat{P}_{\text{post}_t}\right)}{\widehat{P}^2_{\text{post}_t}} + \frac{\text{var}\left(\widehat{P}_{\text{pre}_t}\right)}{\widehat{P}^2_{\text{pre}_t}} - 2\frac{\text{cov}\left(\widehat{P}_{\text{post}_t}, \widehat{P}_{\text{pre}_t}\right)}{\widehat{P}_{\text{post}_t} \times \widehat{P}_{\text{pre}_t}}\right).\end{aligned}$$

If we further assume $P_{\text{pre-}t}$ and $P_{\text{post-}t}$ are independent, this yields

$$\text{var}(EDM_t) \approx \left(\frac{\widehat{P}_{\text{post}_t}}{\widehat{P}_{\text{pre}_t}}\right)^2 \left(\frac{\text{var}\left(\widehat{P}_{\text{post}_t}\right)}{\widehat{P}^2_{\text{post}_t}} + \frac{\text{var}\left(\widehat{P}_{\text{pre}_t}\right)}{\widehat{P}^2_{\text{pre}_t}}\right).$$

The calculation can be simplified by using variance-covariance matrices obtained from Step 4. For instance, instead of taking the ratio, we could work on the linear predictors, for example, η_{post_t}, and η_{pre_t}, and derive the standard errors

Table 2. Descriptive Statistics of Protest Events in DOCA Data (April 1, 1960–September 30, 1995, Complete Observations Only).

Variables	N	Percentage or Mean (s.d. in Parentheses)
Predictors		
Decade of Occurrence		
1960s	7,607	40.14%
1970s	5,996	31.64%
1980s	3,492	18.43%
1990–1995	1,856	9.79%
Size/Number of Participants		
<10	2,866	15.12%
10–49	5,202	27.45%
50–99	2,692	14.21%
100–999	5,826	30.74%
1,000+	2,365	12.48%
Main Form of Contention		
Drama/Ceremony/Other	1,292	6.82%
Legal/Institutional	4,039	21.31%
Picket/Strike	5,633	29.72%
Rally/March	6,075	32.06%
Violence/Conflict	1,912	10.09%
Number of SMOs		
None	10,856	57.28%
One	6,360	33.56%
More than one	1,735	9.16%
Whether Violence Occurred		
No	15,867	83.73%
Yes	3,084	16.27%
Whether Policing Occurred		
No	13,349	70.44%
Yes	5,602	29.56%
President's Party Affiliation		
Democratic	9,145	48.26%
Republican	9,806	51.74%
Governor's Party Affiliation		
Democratic	10,983	57.95%
Republican	7,968	42.05%
Outcome Variables		
N_{Pre01}	**18,951**	0.54(1.20)
N_{Post01}		0.53(1.23)
N_{Pre02}		1.47(2.74)
N_{Post02}		1.47(2.72)
N_{Pre03}		3.20(5.34)
N_{Post03}		3.19(5.34)
N_{Pre04}		5.88(9.26)

Table 2. *(Continued)*

Variables	N	Percentage or Mean (s.d. in Parentheses)
N_{Post04}		5.86(9.24)
N_{Pre07}		11.37(15.68)
N_{Post07}		11.33(15.64)
N_{Pre14}		16.31(21.44)
N_{Post14}		16.24(21.40)
N_{Pre30}		21.01(26.79)
N_{Post30}		20.90(26.75)
N_{Pre60}		30.15(36.91)
N_{Post60}		29.95(36.86)
Valid N	**18,951**	**100%**

and confidence intervals. Suppose a log link function is specified (Poisson or negative binomial model); then,

$$\log(EDM_t) = \log\left(\frac{\widehat{P}_{\text{post}_t}}{\widehat{P}_{\text{pre}_t}}\right) = \eta_{\text{post}_t} - \eta_{\text{pre}_t}$$

$$\text{var}\left(\eta_{\text{post}_t} - \eta_{\text{pre}_t}\right) = \text{var}\left(\eta_{\text{post}_t}\right) + \text{var}\left(\eta_{\text{pre}_t}\right) - 2\text{cov}\left(\eta_{\text{post}_t}, \eta_{\text{pre}_t}\right).$$

Again, if independence between $\eta_{\text{post}t}$, and $\eta_{\text{pre}t}$ is assumed, we have

$$\text{var}\left(\eta_{\text{post}_t} - \eta_{\text{pre}_t}\right) = \text{var}\left(\eta_{\text{post}_t}\right) + \text{var}\left(\eta_{\text{pre}_t}\right),$$

and a 95% confidence interval would be

$$\text{Upper} = \exp\left(\log(EDM_t) + 1.96 \times \sqrt{\text{var}\left(\eta_{\text{post}_t} - \eta_{\text{pre}_t}\right)}\right)$$

$$\text{Lower} = \exp\left(\log(EDM_t) - 1.96 \times \sqrt{\text{var}\left(\eta_{\text{post}_t} - \eta_{\text{pre}_t}\right)}\right).$$

With the EDMs and CIs generated, we can identify the risk factors related to protest diffusion and decline and determine whether their effects are significant.

RESEARCH DESIGN: DATA AND MODELING STRATEGIES

DoCA Data (1960–1995)

As discussed, we need an event-based dataset to analyze protest diffusion using an inter-event approach. The DoCA dataset (McAdam et al., 2009) is ideal for our research purposes. It includes more than 23,000 contentious incidents in the United States, 1960–1995. Each protest is a case in the DoCA data, and most cases contain complete information on the time and location of the protest. Such a data structure allows us to determine the count of protests happening around any given case. In addition to the information on time and location, DoCA data code other characteristics of protests based on reports from several mainstream newspapers in the United States. The characteristics include risk factors such as size, the form of action, diversity of population, number of SMOs involved, and whether policing and violence took place. The DoCA has good quality data and a low rate of missing data. After removing incomplete cases and truncating temporal ranges (April 1960–October 1995), we have 18,951 observations remaining from the original 23,616 entries (80.2% of original cases). The descriptive statistics are shown in Table 2.

Zero-Inflated Poisson Models

As our outcome variables are count variables containing a substantial proportion of zeros and may have overdispersion problems, we need to choose appropriate models for analysis. We follow a two-step procedure, the LRT–Vuong model selection described by Perumean-Chaneya et al. (2013), to choose our initial models. The LRT test results favor negative binomial regression, and the results of the Vuong test suggest the zero-inflated models. However, when predictors are included, some ZINB models become unstable in estimation. Thus, we use ZIP models as the final models. In fitting the ZIP models,[4] we first include the variables of interest in each study (discussed later in the chapter). In addition to the focal predictors, we control the variable of decades in all three studies. The categories are the 1960s, 1970s, 1980s, and 1990s (DoCA data include the years 1960–1995, inclusively). This variable helps to control the long-term trend of social movement activity. Table 2 shows a clear declining trend over the 36 years: social movements in the United States were most active in the 1960s and early 1970s; the overall activity slowed in the 1980s and thereafter. In other words, the overall trend of protests declined over the three and half decades.

STUDY 1: IDENTIFYING RISK FACTORS OF PROTEST DIFFUSION

Study 1 assesses the effects of several commonly studied features of protests on diffusion. We discuss their theoretical relevance and how we operationalize them.

Following our explanation, we identify the significant risk factors associated with protest diffusion or decline.

Study 1 Variables and Operationalization

Size of Protest

One of the most visible features of a protest is how many protestors are present. The number of people involved could be an indicator of the popular support, the effectiveness of mobilization, the friendliness of the environment, and resources available to the protesters (Tarrow, 2011; Zhao, 2004). The size of a protest not only reflects the environment, but it also changes the environment. Large protests may signal political opportunities to latecomers. In other scenarios, large protests may exhaust the accumulated grievances and emotions, the energies of the protesters, popular sympathy and support, and other available resources. To be brief, the protest size could have an encouraging or a discouraging effect on later protests. The DoCA data provide both a continuous and an ordinal measure for protest size; the former has more missing observations, while the latter is more complete. Using information from both variables, we collapse the categories into the following ordinal measures: (1) less than 10 persons; (2) 10–49; (3) 50–99; (4) 100–999; and (5) more than 1,000. We choose the thresholds carefully to ensure every category has enough observations for stable estimation. The size of protests is used as a set of dummy variables in modeling, with the first category serving as the reference group.

Forms of Action

In social movements, how protestors act depends on their demands, resources, skill sets, social, strategies, and adaptation to the physical and social environments. Different forms of action may have different impacts on later protests. Some could be more emotionally charged, inspirational, and stimulating, attracting followers or copycats (Goodwin et al., 2000; Zhao, 2004). Others may require logistical support and consume available resources in the local community within a certain time window, leaving less opportunity for subsequent protestors. It would be interesting to know which forms of action are associated with more protests and which are associated with fewer. The DoCA dataset includes a detailed record of the forms of protestor action. After data cleaning, we group the actions into the following nominal categories: (1) dramaturgical events/ceremonies; (2) legal/institutional actions; (3) rallies/demonstrations/marches; (4) vigils/pickets/strikes; (5) aggressive actions and conflicts. The categories are built based on their face validity, similarities, theoretical relevance, and sample size required for estimation.[5]

Social Movement Organizations

A common research topic in social movement studies is the role of SMOs. The number, activity, and density of SMOs within a national or local community have been associated with the successful spread of a movement's tactics, practices, and frames (Andrews & Biggs, 2006). SMOs can organize protests, maintain social movements, spread information, and network with other SMOs. Importantly, activists belonging to multiple networks can pass on their acquired knowledge from one group to another, leading to learning and the adoption of new tactics and strategies (Meyer & Whittier, 1994). Arguably, then, protests sponsored by SMOs, especially multiple SMOs, are more likely to diffuse. We measure the SMO variable as how many organizations are mentioned in the news report of an event. Since most events have zero or only one SMO, we collapse this numeric measure into a three-level ordinal variable: "no SMO involved," "one SMO," and "multiple SMOs." We use these as dummies in our data analysis; the first category serves as the reference group.

Violence

Violence is another important aspect of protest diffusion (Myers, 2000, 2010). Violence may signal extreme levels of discontent and grievance or negative state-society relations in certain contexts (Myers, 2000; Zhang et al., 2021; Zhao, 2004), and violent protests and conflicts with counter-movements or policing may generate new reasons for further protests, leading to the radicalization of a protest cycle (Steinert-Threlkeld et al., 2022). For example, during the 2010 Toronto G20 Summit Protests, police brutality and arrests on June 26–27 provoked subsequent protests on June 28–29, with protestors demanding justice and the release of jailed protesters. Similarly, during the 2019 Hong Kong Protests, the Prince Edward subway station's conflicts on August 31 became a focal issue that ignited further protests in early September. In other cases, violence may have a "safety valve" function: a violent protest could release the potential for violence in a limited period and generate a relatively peaceful period. In our study, violence is a dichotomous variable recording whether violence occurred in any given event.

Study 1 Method

As discussed previously, we fit ZIP models to predict the numbers of pre- and post-event protests for t equals 1, 3, 7, 14, 30, 45, 60, and 90. Since there are two models for each t, we end up fitting 16 ZIP models. All models include the size of the protest, the forms of action, SMOs, and violence as predictors, with decades controlled for. We calculate the EDMs and CIs based on the models and visualize them in Fig. 1. In the figure, all x-axes range from day 1 to day 90 (t); all y-axes are EDMs ranging from 0.7 to 1.3, and most EDM values are distributed around 1. EDMs whose lower bounds are significantly higher than 1 signify "diffusive"; EDMs whose upper bounds are significantly lower than 1 signify "self-limiting"; the insignificant ones are in dark grey.

Study 1 Results

Fig. 1a displays the effects of the size of protest on EDM. It shows that the groups of "50–99" and "100–999" are mostly diffusive ones, especially when t

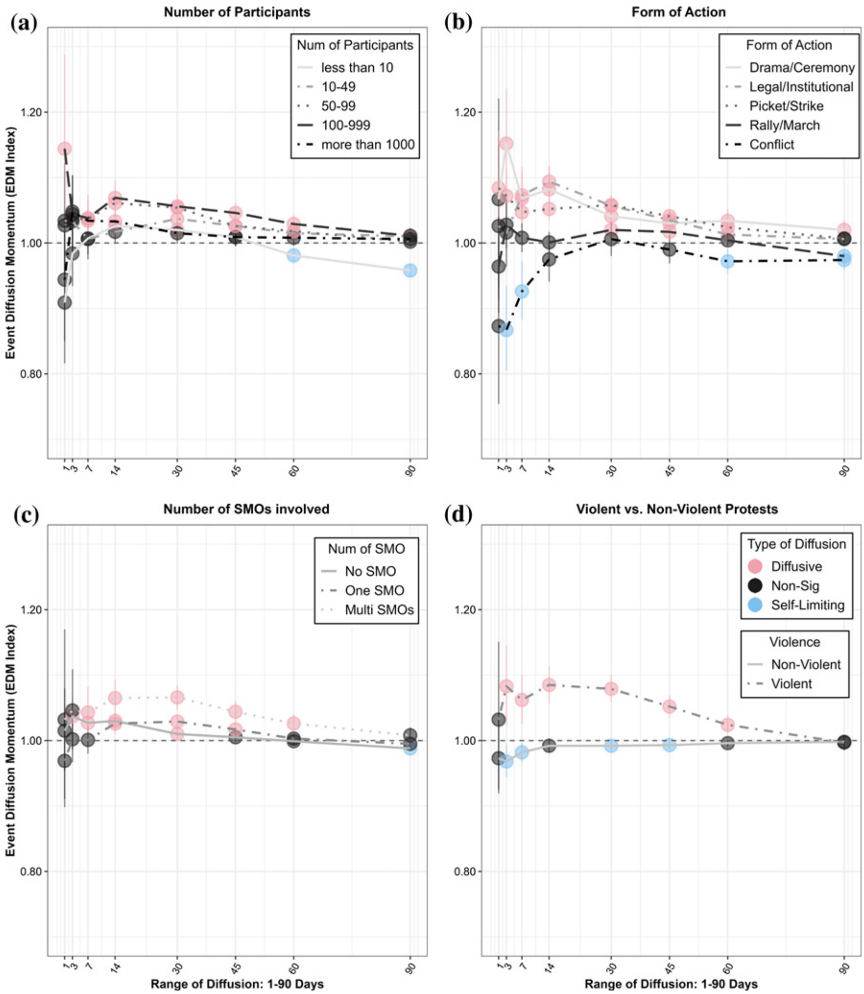

Fig. 1. EDM Predicted by Protest Features (Study 1).

ranges from day 1 to day 60. In contrast, small-scale protests with fewer than 10 persons tend to decline over the long term ($t > 45$). Briefly stated, mid-sized protests tend to diffuse, while small ones tend to decline, and large ones are indifferent to later diffusion.

The next variable of interest is the form of action (Fig. 1b). When protestors adopt dramaturgical strategies, picketing, strikes, and institutional actions, protests tend to increase in the following days (t = 1–60). However, when protestors engage in conflict, there are fewer protests in the next few days ($t = 3$ and $t = 7$) and also in the long run ($t = 60$ and $t = 90$). This may be related to repression in the short term and exhaustion of resources in the long term.

Fig. 1c shows how numbers of SMOs involved in a protest predict EDMs. Consistent with previous findings on the roles of SMOs, protests with one or multiple organizations tend to diffuse, and this tendency lasts from day 1 until day 60. Protests without SMOs diffuse less and start to decline sooner than the organized ones.

Fig. 1d displays the effects of violence on diffusion. We find violent protests tend to diffuse right away, and the effect lasts from day 3 to day 60. In contrast, non-violent protests tend to decline from day 3 to day 45. This finding is consistent with the assumption that violence can trigger emotions and lead to future mobilizations.

STUDY 2: US PRESIDENTS' AND GOVERNORS' PARTY AFFILIATIONS AND DIFFUSION

Study 2 Variables

Party Affiliation

Social movement researchers care about the social environment in which protests occur. For example, political opportunity theory pays attention to how contextual factors and activists interact in social movements. The opportunities related to the success or failure of movements include political access, repression, elite cleavages, international and domestic allies, and so on (Goldstone, 2004). Therefore, the political leaders at both central and local levels should be highly relevant to protest diffusion. In the United States, party affiliations have important implications for the political opportunity structure. At the federal level, a President's policies on civil rights, gun control, global warming, foreign affairs and wars could all provoke discontent and contention; at the state level, a Governor's partisanship will have a similar impact on movement mobilization. The differences between Democratic and Republican politicians at either level may yield different results in protests.

Moreover, there may be interactions between the federal- and state-level leadership. Electing a Democratic or Republican President (or Governor) signals the political atmosphere at different levels. The macro- and meso-environments may interact and generate consequences for protestors. First, when opposing parties hold federal and state offices, there may be more reasons to protest. Progressive people may feel greater grievances under a conservative President and vice versa. Second, when the President and Governor are in opposing parties, there might be more elite cleavages from which protestors could benefit. Local leaders may be more reluctant to repress a movement or may even encourage and utilize protest as leverage against their rivals in Washington DC. All these lead to our expectation that partisanship could be associated with protest diffusion.

Study 2 Method

We find the records of all Presidents' and Governors' party affiliation (Democratic vs. Republican)[6] during 1960–1995 and match the party alignment information with the DoCA data by location and date of protests. We fit 16 ZIP models as previously discussed. We include decades as a control variable for each model, the President's party, the Governor's party, and an interaction term between them. We calculate the EDMs and CIs, as displayed in Fig. 2.

Study 2 Results

Fig. 2 shows the effects of the President's and Governor's party affiliations on EDM. None of the EDMs is significantly different from zero in the short term, but in the long term (t = 45, 60, 90), party affiliation begins to make a difference. Under Democratic Presidents and Democratic Governors, protests tend to decline when $t = 90$; similarly, for Republican Presidents and Republican Governors, protests decline when t = 45, 60, 90. However, an interesting pattern emerges for the combination of Democratic Presidents and Republican Governors: in such cases, protests tend to diffuse (t = 60, 90). Although Republican Presidents and Democratic Governors do not have similarly interesting chemistry (EDMs are insignificant), the diverging trend applies (the gap in Fig. 2b is significant for $t = 90$). To sum up, when different parties hold federal and state offices, protests tend to diffuse; when offices are held by the same party, protests tend to decline, lending support to the argument of elite cleavage effect.

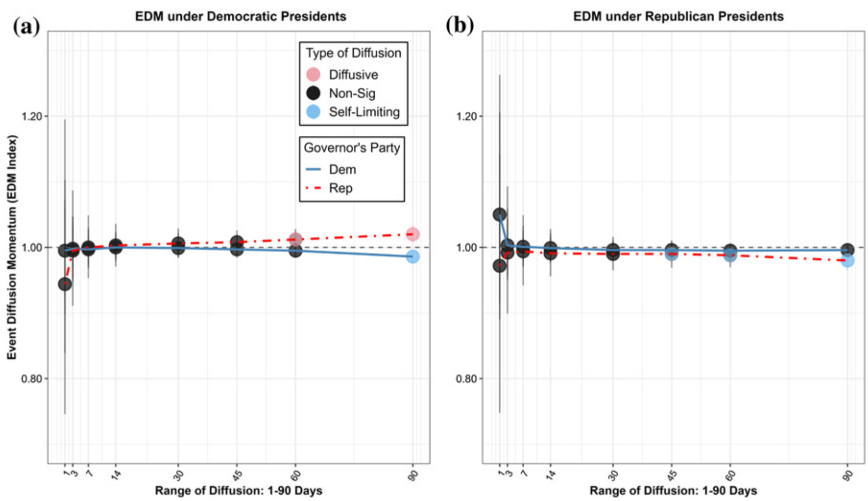

Fig. 2. EDM Predicted by Presidents' and Governors' Party Affiliation (Study 2).

STUDY 3: MACRO-MICRO ANALYSIS OF EFFECTS OF GOVERNORS' PARTY AFFILIATIONS AND POLICING

Study 3 Variables

Policing and repression have an impact on protests and their diffusion. In some cases, repression prevents further mobilization (Zhao, 2004), but in other cases, it provokes a larger scale of subsequent protests (Brym et al., 2014). Suh et al. (2017) recently found the ability of repression to stop diffusion depends on the presence of social media. The decision on policing is often made by executive leaders, such as Presidents or Governors in the United States. In most situations, protests without immediate risk of escalation either see no policing or face some moderate level order-maintaining effort; others are confronted by police or National Guards, both of which are at a Governor's disposal. Thus, analyzing how a Governor's party affiliation interacts with policing to predict EDM may shed light on how social contexts shape the protest diffusion process. Acting on this assumption, we match Governors' party affiliation information from 1960 to 1995 with the DoCA data. We calculate the predicted values, EDMs, and CIs of the interaction terms from the ZIP models. The effects are visualized in Fig. 3.

Study 3 Results

Fig. 3a displays EDMs under Democratic Governors. Most of these EDMs are insignificant; no matter whether there is policing or not, the momentum does not vary for the most range (t from 1 to 45). The only exception is protests under policing (t = 90), showing that they are self-limiting in the long run. For the Republican Governors (Fig. 3b), policing plays a bigger role in shaping protest

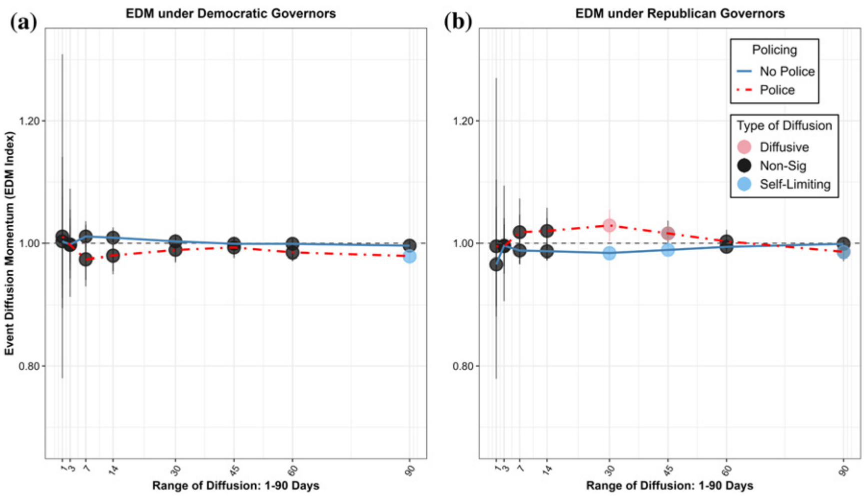

Fig. 3. EDM Predicted by Governors' Party Affiliation and Policing (Study 3).

diffusion: policing is associated with more protests afterward (t = 30 and 45), and the absence of policing is associated with fewer protests afterward (t = 30 and 45). In other words, policing plays different roles in different political contexts; it leads to protest diffusion under Republican Governors and protest decay under Democratic Governors. This suggests either different governance styles or state-society relations in red and blue states.

DISCUSSION AND CONCLUSION

Previous studies on protest diffusion have mainly looked at the environments and networks in which diffusion takes place. The protest features and how they affect the inter-protest diffusion dynamics have received less scholarly attention, and their study lacks standardized methodological practices. Borrowing wisdom from epidemiology and criminology, we suggest viewing all protests as potentially contagious and investigating factors related to their contagiousness. In this paper, we propose a method to estimate the event diffusion momentum (EDM) and its confidence interval. We define protest diffusion as more subsequent protests than precedent ones within a certain temporal and spatial range, or in our notation, $N_{\text{pre-}t} < N_{\text{post-}t}$. Similarly, social movement decay is defined as $N_{\text{pre-}t} > N_{\text{post-}t}$. The EDM is simply the ratio of $N_{\text{post-}t}$ to $N_{\text{post-}t}$ (or that of the predicted values, $P_{\text{post-}t}$ to $P_{\text{post-}t}$).

We illustrate the use of our method in three separate studies: the first on the effects of protest features, the second on the effects of political leaders' partisanship, and the third on the effects of interaction between leaders' partisanship and policing on protest diffusion. The three studies yield the following findings: mid-sized protests (50–99, 100–999) are more diffusive than smaller and larger ones; dramaturgical protests are more diffusive than other forms, supporting the importance of symbolic actions and signaling in contentious politics; organized protests are more diffusive and enduring than unorganized ones; violence provokes more subsequent protests, while peaceful protests are largely self-limiting; when US Presidents and Governors come from different parties, protests tend to diffuse, supporting the political opportunity theory's argument on elite cleavages; lastly, under Republican Governors, policing generates protest diffusion.

The empirical findings may shed light on some unresolved debates in social movement studies. Take resource mobilization theory as an example. Previous work argues the lack of resources leads to inactive social movements, while abundant resources result in lively ones (Tarrow, 2011). Our findings support this argument. We find large-scale protests are less diffusive than mid-scale protests, possibly because they exhaust available resources within a short time window, thus demobilizing other protests which could otherwise have taken place. Similarly, we find multi-SMO protests are the most diffusive, confirming the role played by organizations and networks in protest diffusion. Our finding that violence leads to more protests is consistent with previous works on emotions and political opportunities (Goodwin et al., 2000; Myers, 2010). Our analyses provide more than just empirical verification of existing works. They also illustrate and establish a methodological practice to empirically test the existing and future theories. In addition to quantitatively studying protests, our proposed method could identify risk factors and suggest new directions for qualitative research. For instance, Study 2 and Study 3 highlight the importance of cross-party conflicts in shaping protest diffusion. Future researchers could explore historical archives to further reveal how US Presidents and Governors make decisions when facing protests, especially when they are political rivals.

The paper has some limitations that should be acknowledged. First, the proposed method demands comprehensive and unbiased data on events. Although the DoCA data are widely used in social movement research, they suffer from the specific bias for using the *New York Times* as the source (Ortiz et al., 2005; Weyland, 2019). For example, violent protests usually receive more media attention. Similarly, protests invoking national grievances or targeting federal-level policies may be covered more than those driven by local issues, and protests in New York are recorded more than elsewhere. However, our primary goal is to exemplify the use of a newly proposed method; the bias of news source is not a main concern, given our research scope. When it comes to other settings, such as authoritarian contexts where patterns of omitted observations are more influenced by power, censorship, and other social mechanisms (Göbel & Steinhardt, 2022), the bias of media data should be treated with more caution. Future researchers could apply the proposed method to more comprehensive, better-quality data generated with techniques such as neuro networks from texts, images, videos, and other sources (Hanna, 2017; Zhang & Pan, 2019).

Second, we only consider diffusion within state borders rather than using geographical distances as ranges. It would be helpful to consider spatial patterns, such as incorporating the geographical proximity and network structures into the study of diffusion (e.g., Wang & Soule, 2012). Third, we did not assess the effects specific claims and grievances on diffusion for their high missing numbers. Future research could improve on ours with better datasets. Lastly, we assume homogeneity and equivalence of each observation and assign all observations equal weights. We acknowledge this is unlikely to be true in reality – protests with common concerns are more likely to influence each other; significant events are more impactful than others. That being said, some work finds protests are often inspired by previous protests even when they do not share the same concern or target (Wang & Soule, 2012). Schneiberg and Lounsbury (2017) call this "diffusion by adaptation", by which they mean different activists and organizations may be pressured toward assimilation and isomorphism under the same environmental constraints. Therefore, our assumption that diffusion could happen between any types of protests is not ungrounded.

Our method has several advantages. First, it relies on minimal assumptions and employs only objective information, such as the location and time of protests or the numbers of events happening before and after each protest. This naïve operationalization ensures little subjective bias is introduced by the researcher. Second, EDM is straightforward, intuitive, and easy for interpretation. Protest diffusion is simply when EDM > 1; the opposite, protest decline or decay, is simply when EDM < 1. Thus, EDM helps to operationalize the "rises" and "falls" within cycles of protests. We could use EDM to capture clusters of protests and identify the initiator and spin-off protests (McAdam, 2013) or to understand both mobilization and demobilization processes. We could also say "Factor A", "Variable B", or "Environment C" is associated with protest diffusion or decay after getting their corresponding EDMs.

Third, EDMs are comparable across contexts. By using ratios of cases instead of differences in the raw numbers, we exclude the effects of any contextual differences. These contextual differences include spatial or temporal variations in the scale of social movements (e.g. 1960s vs. 1990s in the USA; social movement liveliness in democracies vs. dormancy in autocracies (Zhang, 2016). In other words, EDMs from Paris in 1968, Toronto in 2010, and Moscow in 2022 can be put together, compared, and discussed. Fourth, our approach converts the analysis of protest diffusion into a conventional multivariate approach. Within the same regression model, we can simultaneously identify the macro-, meso-, and micro-level risk factors and study their interaction effects on diffusion. Lastly, this method is not merely applicable to protest diffusion research; it can assist scholars studying the diffusion of other social facts and events. For the above reasons, we invite scholars to apply the proposed method to different empirical cases other than American protests. We anticipate such endeavors could further our understanding of diffusion.

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NOTES

1. Reproducible codes, data, appendices and supplementary information can be accessed via the GitHub repository: https://github.com/huiquanR/2022_Event_Diffusion_Momentum.

2. Since the maximum value of t is 90 days, we need to truncate the data by 90 days at both ends of the temporal range (April 1, 1960–September 30, 1995) to ensure all observations' $N_{\text{post-}t}$ and $N_{\text{pre-}t}$ are consistent and comparable.

3. We use predicted values ($P_{\text{post-}t}$ & $P_{\text{pre-}t}$) instead of raw numbers of observations ($N_{\text{post-}t}$ & $N_{\text{pre-}t}$) mostly because of the frequency distribution of events. Many observations in DoCA are "isolated" protests and there are many zeros in their $N_{\text{post-}t}$ & $N_{\text{pre-}t}$, and this does not support the calculation of quotients. Therefore, we fit zero-inflated Poisson (ZIP) models first and then calculate quotients based on the predicted values from ZIP models. We thank the anonymous reviewers for raising this concern.

4. Considering the length of the paper, we only present the visualized results from the models and put the regression results in the online appendices via the link of https://github.com/huiquanR/2022_Event_Diffusion_Momentum.

5. The first category contains performances, plays, and other eye-catching symbolic actions; the second includes the most institutionalized actions of all categories. We tried to

construct differently for certain sub-categories as a robustness check, and it did not change the main patterns reported in this paper.

6. To simplify the analysis and interpretation, we collapse the few independent politicians into either the Democratic or Republican category according to their orientations.

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