

Diffusion of Protests: Toward an Inter-Event Approach

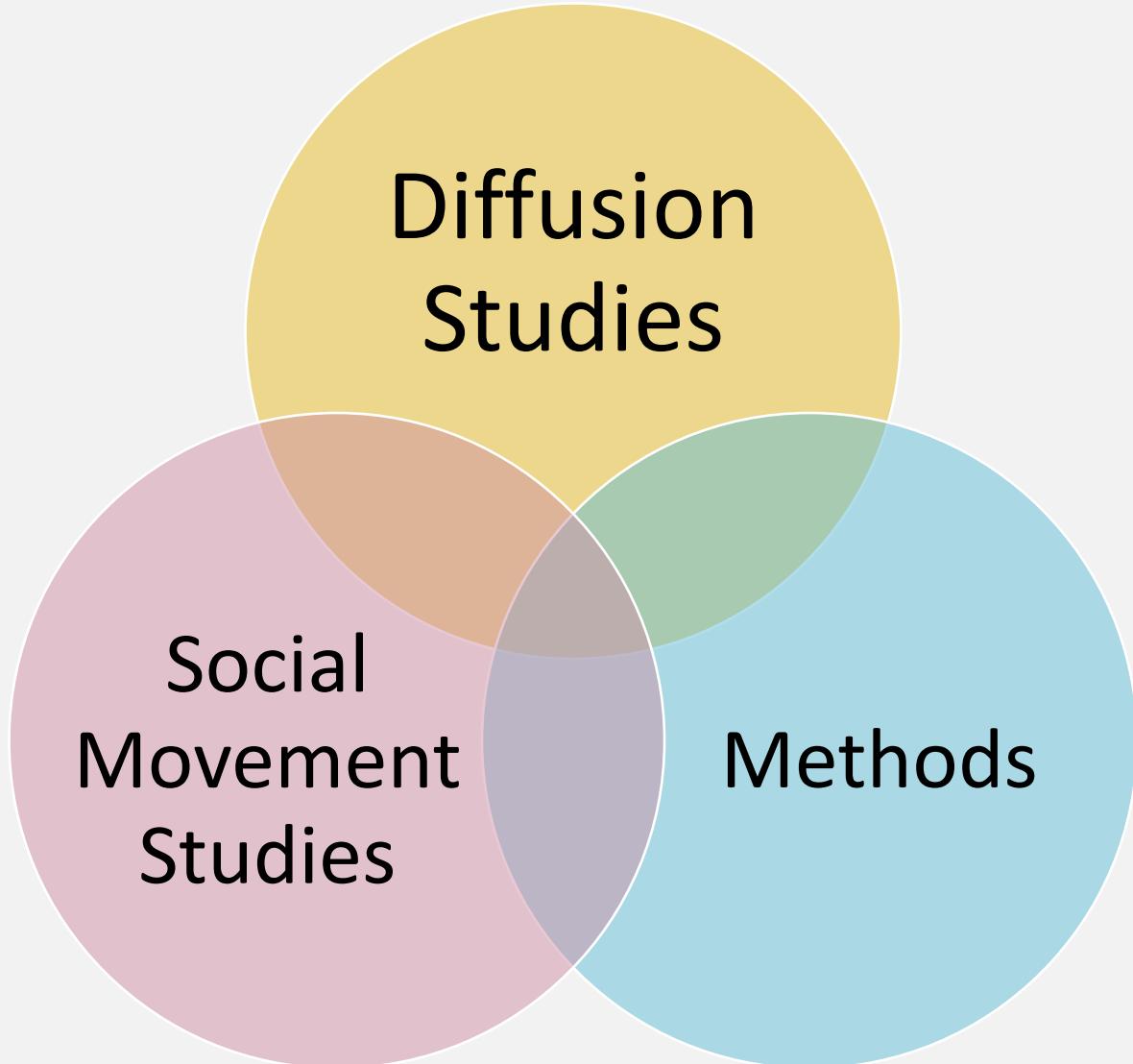
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- Zhang & Cai (2021).
 - Tony Huiquan Zhang & Tianji Cai. (2021). “Measuring Event Diffusion Momentum (EDM): Applications in Social Movement Research”, manuscript under review.



Outline

- **Intro**
 - *Diffusion Studies in General*
- **Context**
 - *Social Movement Studies about Protest Diffusion*
- **Research Design**
 - *A 5-Step Method for “Event Diffusion Momentum”*
- **Analysis**
 - *Data, Variables and ZIP/ZINB Models*
- **Findings**
 - *Results from Three Studies*
- **Discussions**
 - *Implications and Future Agenda*

Introduction

Diffusion is Not New

- History/Historical Geography
 - Population Migration (Quintana-Murci et al. 1999. *Nature Genetics*)
 - Wars & Conflicts (Beardsley. 2011. *Journal of Politics*)
 - Political Expansion (Weyland. 2010. *Comparative Political Studies*)
- History of Science/Technology
 - Language, Writing Systems, Symbols, Numbers and Notations...
 - (Rickford. 1986. *Language*; Hoffer 2002; Durbin 1971)
 - Tales, Stories, Legends, Beliefs, Religion, and Ideology...
 - (Porter 2004; LaFree et al. 2018; Starr 1991)
 - Technology and Innovations...
 - (Stoneman & Diederend. 1994. *The Economic Journal*; Abrahamson & Rosenkopf. 1997. *Organization science*)

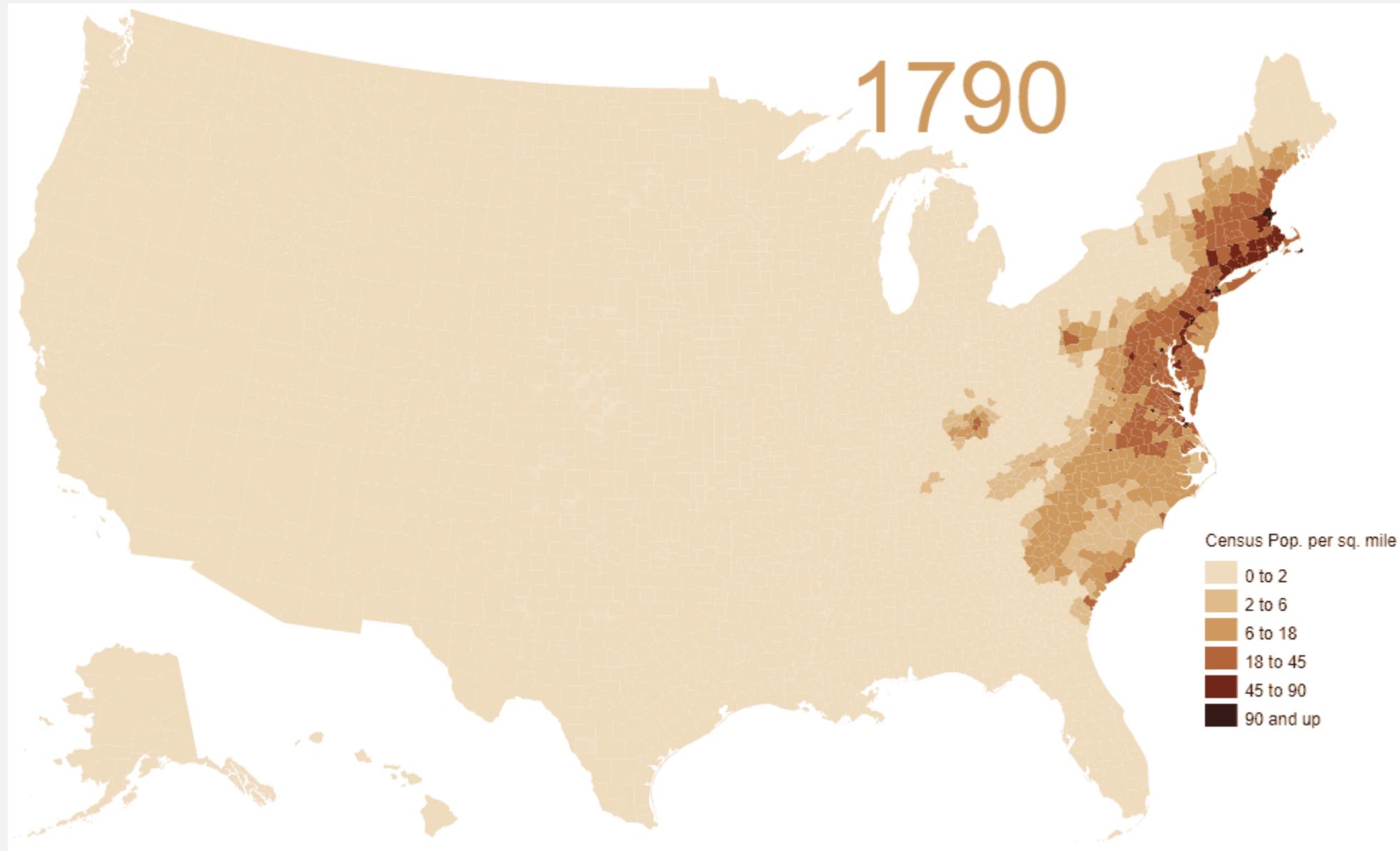
Political Expansion



- Source:
- https://commons.wikimedia.org/wiki/File:Zh-Territories_of_Dynasties_in_China.gif

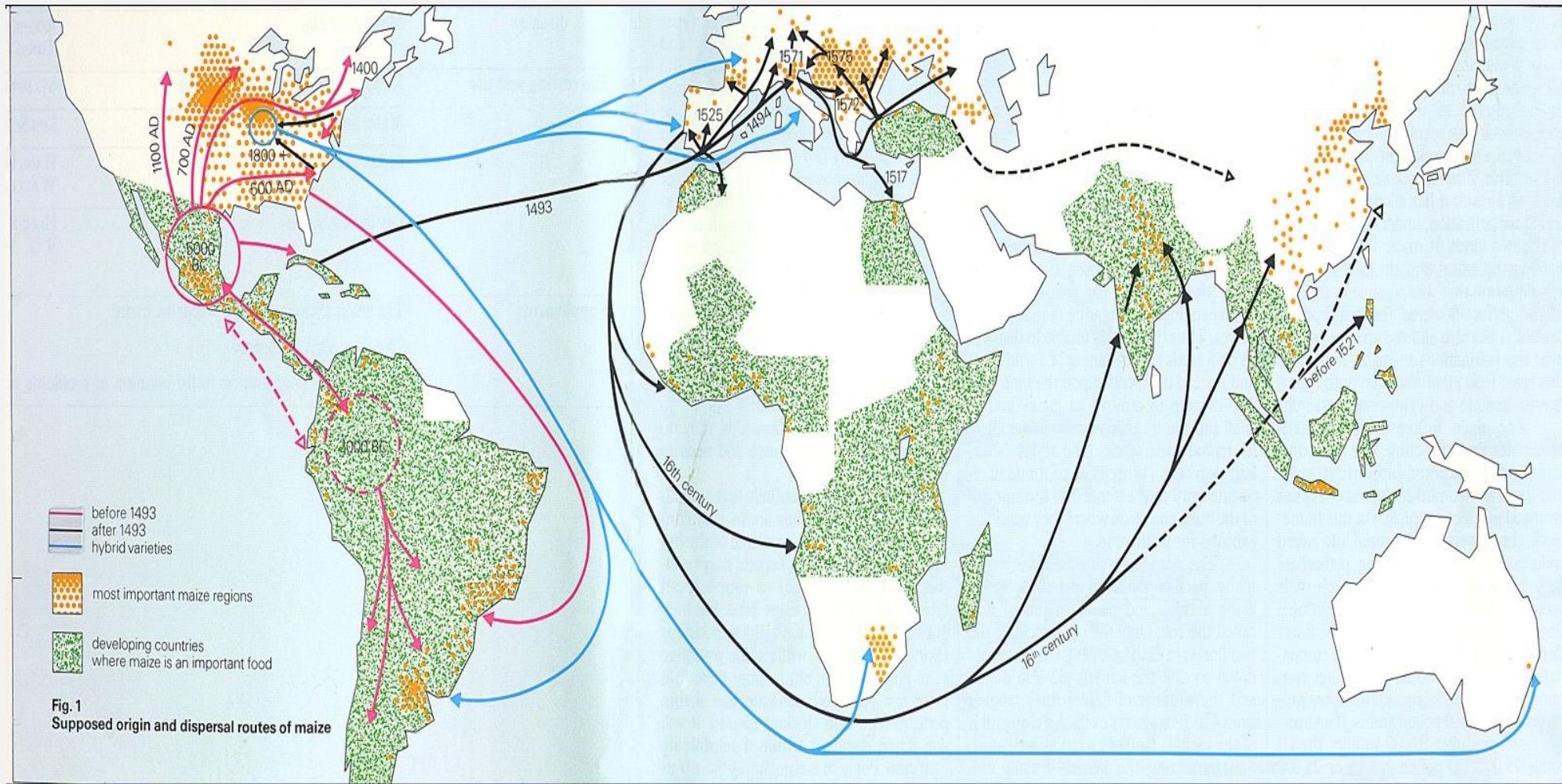
Population Diffusion

- Source:
- Vividmaps.com

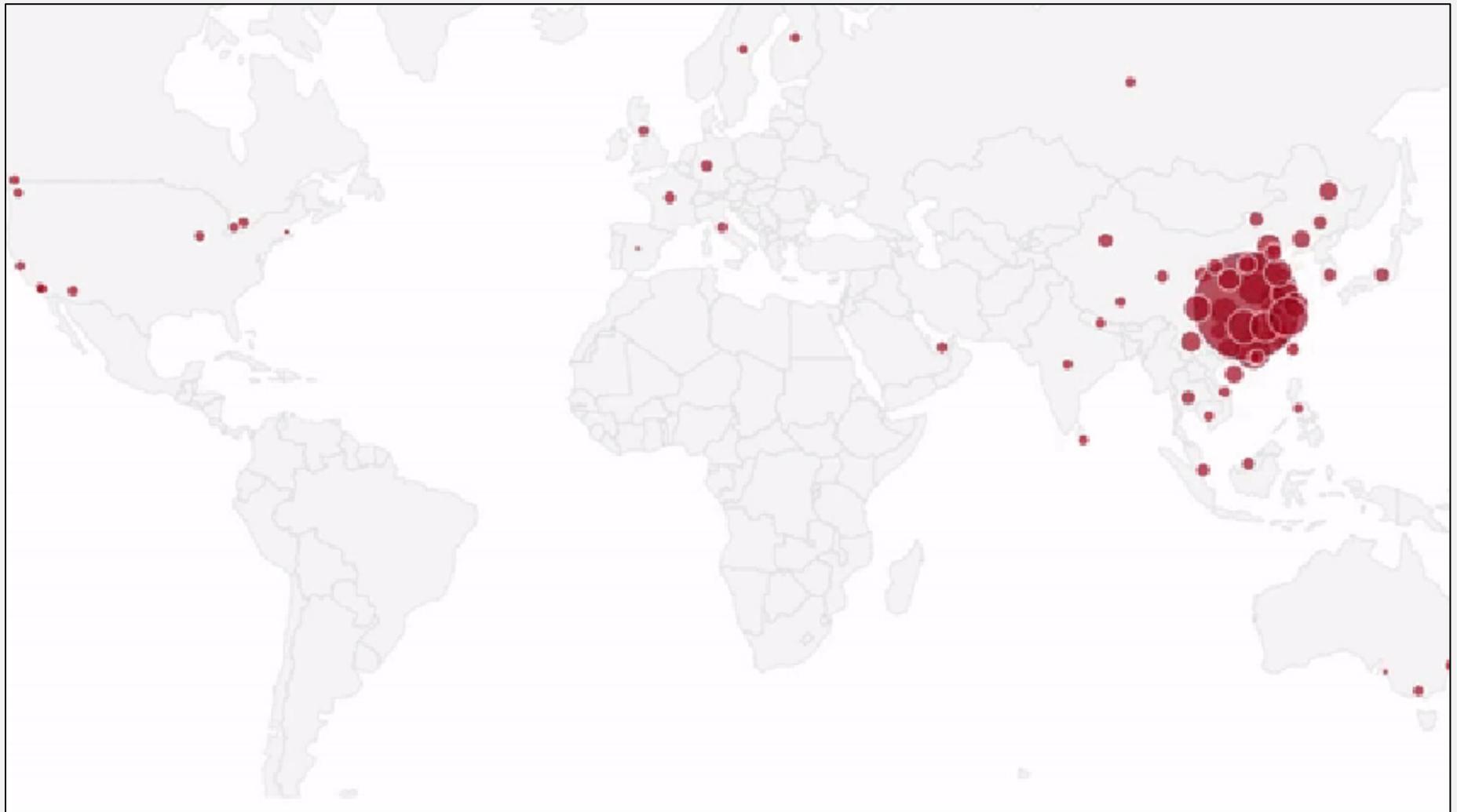


Spread of Corn

- Image Source:
- <https://digital.library.illinois.edu/items/dd6d47c0-0d92-0135-23f6-0050569601ca-1>



Diffusion of COVID-19



- Source:
- <https://digital.library.illinois.edu/items/dd6d47c0-0d92-0135-23f6-0050569601ca-1>

Diffusion Studies

- Diffusion has been an important topic in many disciplines - both natural and social sciences.
- Biology, Epidemiology and Public Health
- Social Sciences
 - Management/Business
 - *Financial and Business Models, Organizations, Management Practices...*
 - *Brands, Fashion, Innovations, Consumer Behaviors*
 - Politics/Sociology/Public Administration
 - *Diffusion of Pop Culture, Ideology, ...*
 - *Adoption of Policies, Institutions and Laws...*
 - Criminology...
 - *Crimes – especially copy-cats*

What is diffusion?

Diffusion Studies

- Diffusion:
 - The movement of people/objects/actions/events over time and space (from A to B);
 - or, the adoption of practice/innovation/technology/institutions over time (from 0 to 1).
- Usually – Expansion in space & time / Rise in numbers
- The opposite process: decay

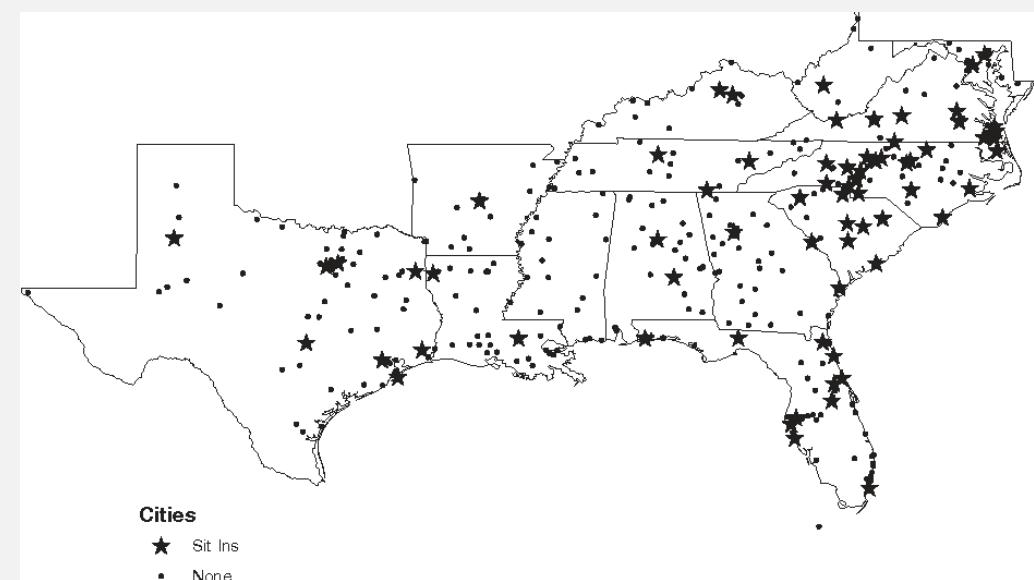
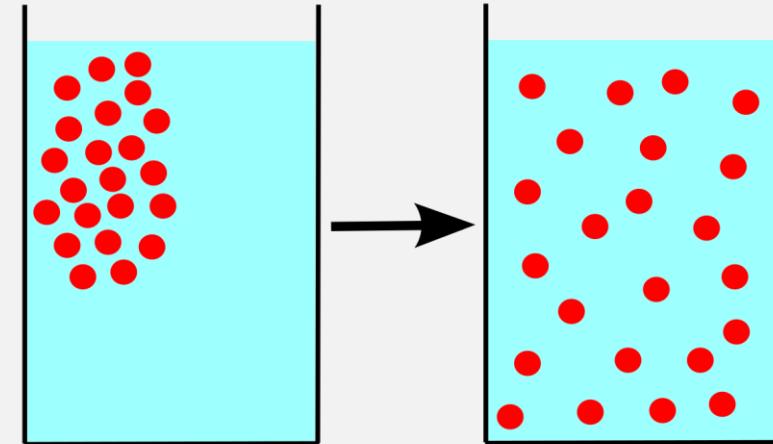


Image source: Andrew & Biggs 2006.

Two Types of Diffusion

- Cumulative and non-cumulative diffusion
- Cumulative Examples:
 - Writing, Printing, Telephone, Railway, Women's Voting Rights, Vaccination
- Non-cumulative Examples:
 - Wars, Conflicts, Protests, Crimes

The Diffusion of the Movable Type Printing Press

A: Cities with Printing in 1450



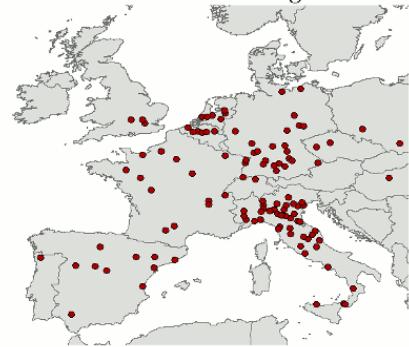
B: Cities with Printing in 1460



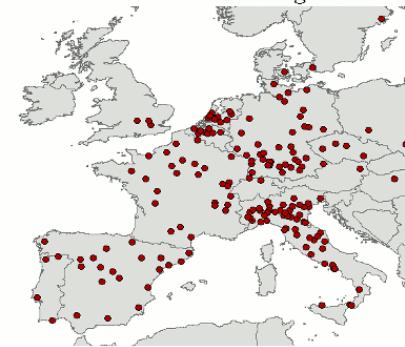
C: Cities with Printing in 1470



D: Cities with Printing in 1480



E: Cities with Printing in 1490



F: Cities with Printing in 1500

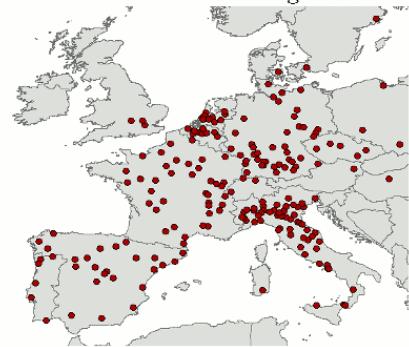


Image source: Dittmar 2011.

Diffusion Studies in Business & Management

- Usually cumulative models.
- Diffusion of technological innovation, organizational practices, new product acceptance...
- Innovation Diffusion Models
 - Mahajan, V. (2010). Innovation diffusion.
 - Söderholm, P., & Klaassen, G. (2007).



ADOPTION CURVE

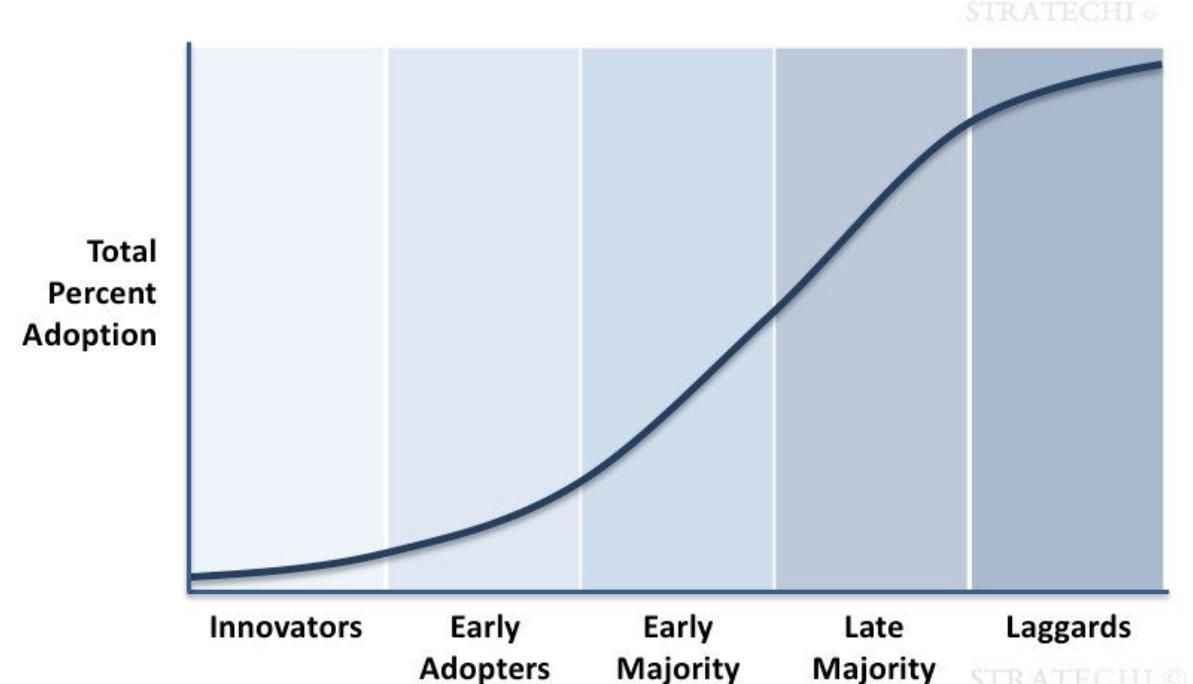
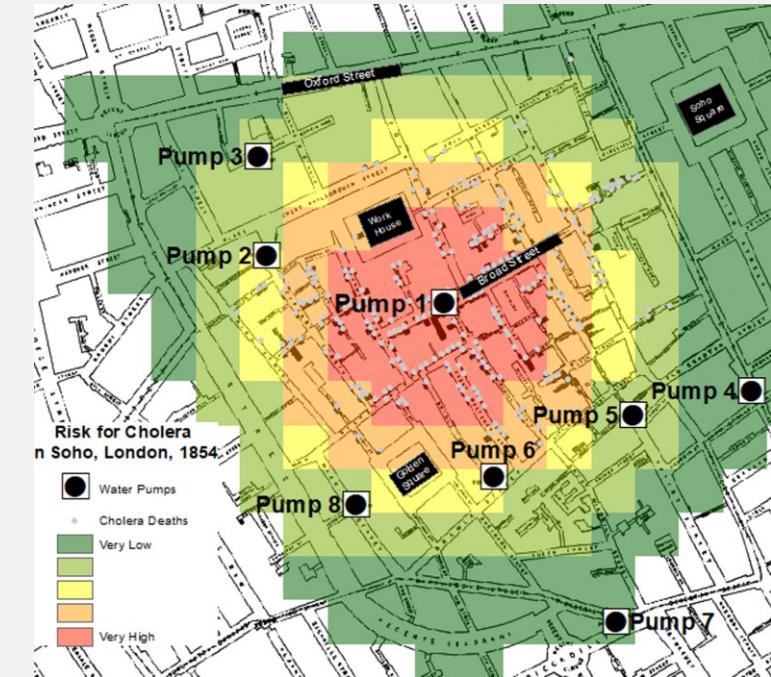


Image source: Stratech.

Epidemiology and Public Health

- Diffusion of diseases
 - E.g. London Cholera Outbreak in 1854
- Spatial Models
- Temporal Models
- Spatial-Temporal Joint Models



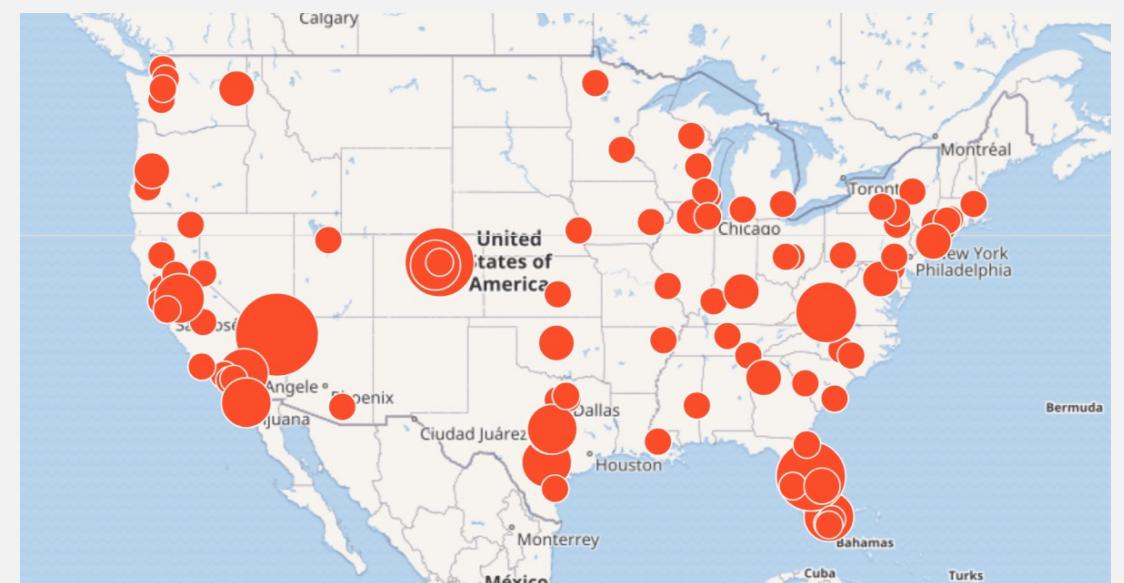
图源：游戏《瘟疫公司》

Criminology

- Diffusion of Crimes
 - Copy-cat Crimes
 - 1993 Wave of Air Hijacking (Miller 2007)
- Mechanisms and Explanations
 - Holden, R.T. (1986 - AJS). The contagiousness of aircraft hijacking.
- “Social Contagion”
 - Emotion – Mass Shooting, Suicide
 - Information
 - Inspiration
 - Signaling (Broken Windows Theory)



1993 Air Hijacking Waves in China, NY TIMES



Mass Shootings in USA Image Source: PBS.org

Context

Social Movements and Diffusion

Social Movements and Diffusion

- It is agreed that social movements diffuse.
 - The protests themselves diffuse (Andrews & Biggs 2006 - ASR)
 - E.g. *Civil Rights Movements; Occupy Wall Street Movement; Me-Too Movement*
 - Elements of protests, such as repertoire, strategy, framing and ideology, networks and organizations, personnel and resources, diffuse as well. (Soule 2004)
 - E.g. *Flash Mob (快闪) & #HashTag# as a Protest Action*
 - Emotions and ideology could spread – via direct [friends, networks, organizations] or indirect links [news, media, and social media]

How Protests Diffuse?

- Direct Diffusion (Soule 2004; Wang & Soule 2012)
 - Actual connection through people, networks, organizations
- Indirect Diffusion (Goldstone 2004; Weyland 2019)
 - No actual connection – but behave similarly
 - When actors face similar structural pressure, they act accordingly and consequently, their action will become similar.
 - Structural Isomorphism (结构同化、同构)
 - It is argumentative that whether this should be considered diffusion; however, it is true that they will show high correlation and temporal-spatial adjacency. (相关、时空邻接)

Research Gaps (I)

- However, there are some gaps in existing studies of protest diffusion.
 - Too much on context, too little on actions;
 - Too much on when/where/how it diffuses, and too little on “What” diffused
 - *Political Opportunity Theory, Resource Mobilization Theory*
 - *The context, environment, and “field” for diffusion to occur is paid much attention to, but not enough has been paid to the inter-movement dynamics, especially the features of each protest.*

Research Gaps (2)

- However, there are some gaps in existing studies of protest diffusion.
 - Methodological Generalizability
 - *There has not been a widely accepted methodological practice in the field.*
 - Researcher's Bias
 - *Definition & Operationalization (Measurement)*
 - *Ad Hoc; Post Hoc; Subjectivity. (E.g. “Opportunity”, “Elite Division”, “Network”, and even outcome of protest is argumentative – what is a successful/failed protest?...)*

We suggest... (I)

- Turn to Events
 - Turning to the inter-event dynamics of diffusion (Holden 1986)
 - “toward an eventful sociology” (Sewell 1996)
 - “sequence of protests” (Minkoff 1997)
 - Temporal-spatial joint models (Andrews & Biggs 2006; Myers 2010)
- Borrowing wisdom from public health and criminology; focusing on objective information of each event, and how these features affect diffusion.
 - E.g. what kinds of patients/viruses are more contagious?
 - E.g. what kinds of protests are more diffusive?

We suggest... (2)

- Avoid Unnecessary Assumptions and Prerequisites
 - Does diffusion effect always decay (Andrews & Biggs 2006 ASR; Strang 1993 ARS) over time? Not necessarily.
 - - *our method allows either diffusion and decay.*
 - Could unconnected individuals/actors be influenced by each other? Yes. (Mass media & Internet)
 - - *our method assumes all cases could have a potential impact on later actors.*
- Analyze with a standardized methodological practice

Research Method

Table 1 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: Count the number of pre/post-event protests within the ranges;	$N_{\text{pre-}t}; N_{\text{post-}t}$
Step 4: Fit appropriate count models and get predicted values for each risk factors;	$P_{\text{pre-}t}; P_{\text{post-}t}$
Step 5: Calculate the ratios as the EDMs and CIs.	$\text{EDM}_t = P_{\text{post-}t}/P_{\text{pre-}t}$ <i>(CI formula see discussions below.)</i>

(I) Event-Based Data

- Event as observations/cases.
- Time/Location Information Available
 - for Counting adjacent cases, both temporally and spatially
 - Time: Can be as accurate as month, date, or even sec/min/hr (especially for modern automated big data generation techniques, see Hanna 2017)
 - Location
 - *Longitude, Latitude;*
 - *City/Province/Zipcode/State (depends on what your question is)*

(2) Define the Spatial/Temporal Ranges

- Spatial
 - Geographic distance? A circle with radius of n kilometers.
 - Within the same state. Why?
- Temporal
 - $t = 1\text{-}90$ days
 - April 1, 1960 – Sep 30, 1995



(3) Count the Protests Before/After Each Case

	CASEID	STATE	POL	VIO	DATE	SIZE	PostAct30	PostAct60
1	CASE_000027	new york	0	0	1960-09-14	10	42	56
2	CASE_000162	tennessee	3	0	1960-03-02	50	9	16
3	CASE_000163	tennessee	3	0	1960-03-02	7	9	16
4	CASE_000164	alabama	0	0	1960-03-04	900	17	18
5	CASE_000165	south carolina	3	0	1960-03-04	26	13	13
6	CASE_000166	north carolina	0	0	1960-03-04	10	9	13
	CASEID	STATE	POL	VIO	DATE	SIZE	PostAct30	PostAct60
19156	CASE_023511	new york	0	0	1995-05-13	2	7	14
19157	CASE_023514	new york	0	0	1995-11-01	50	11	22
19158	CASE_023517	michigan	0	0	1995-11-01	1000	0	0
19159	CASE_023585	new york	0	0	1993-12-15	4	2	7
19160	CASE_023598	new york	0	0	1995-10-16	100	16	27
19161	CASE_023604	california	0	1	1995-08-23	1	4	6

(4) Predict with ZIP models

- Count Models
 - DV's values are natural numbers: 0, 1, 2, 3, ...
 - To count stuff. (e.g. How many apples you harvested today? How many 911 calls in the past hour? How many traffic violations in this street today?)
- Commonly used types
 - Poisson, Negative Binomial (NB), Zero-inflated Poisson (ZIP) and Zero-inflated Negative Binomial (ZINB)
 - NB: over-dispersion
 - ZI: excessive zeros
- Why ZIP?

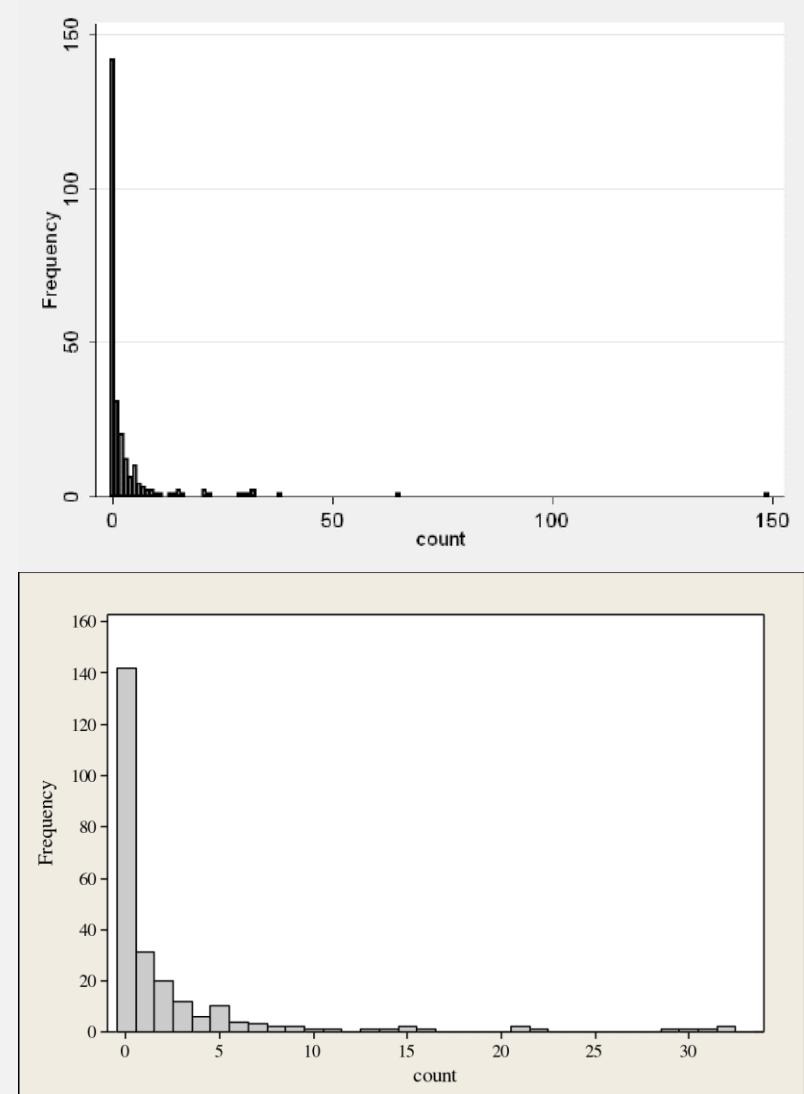


Figure 1: Histograms of the response variable

Appendix Table 1 Predicted Counts of Precedent Protests (P-pre t) from ZIP Models (Standard Errors in Parentheses)

	Model 1 Pre ₀₁	Model 2 Pre ₀₂	Model 3 Pre ₀₃	Model 4 Pre ₀₄	Model 5 Pre ₀₇	Model 6 Pre ₁₄	Model 7 Pre ₃₀	Model 8 Pre ₆₀
Count model: (Intercept)	0.41 *** (0.04)	0.93 *** (0.03)	1.17 *** (0.02)	1.35 *** (0.02)	1.72 *** (0.01)	2.18 *** (0.01)	2.71 *** (0.01)	3.23 *** (0.01)
Count model: DECADE70s	-0.18 *** (0.03)	-0.19 *** (0.02)	-0.17 *** (0.01)	-0.17 *** (0.01)	-0.15 *** (0.01)	-0.12 *** (0.01)	-0.05 *** (0.00)	0.02 *** (0.00)
Count model: DECADE80s	-1.06 *** (0.08)	-1.04 *** (0.04)	-1.00 *** (0.03)	-0.97 *** (0.03)	-0.95 *** (0.02)	-0.89 *** (0.01)	-0.87 *** (0.01)	-0.84 *** (0.01)
Count model: DECADE90s	-0.73 *** (0.08)	-0.76 *** (0.05)	-0.74 *** (0.04)	-0.71 *** (0.03)	-0.68 *** (0.02)	-0.64 *** (0.01)	-0.62 *** (0.01)	-0.60 *** (0.01)
Count model: LOGSIZE	-0.04 * (0.02)	-0.03 ** (0.01)	-0.02 * (0.01)	-0.02 ** (0.01)	-0.02 ** (0.00)	-0.02 *** (0.00)	-0.01 *** (0.00)	-0.01 *** (0.00)
Count model: FORMRally/March	0.09 ** (0.03)	0.09 *** (0.02)	0.07 *** (0.02)	0.08 *** (0.01)	0.07 *** (0.01)	0.08 *** (0.01)	0.07 *** (0.01)	0.05 *** (0.00)
Count model: FORMDrama/Ceremony/Other	0.24 *** (0.05)	0.14 *** (0.03)	0.10 *** (0.03)	0.14 *** (0.02)	0.12 *** (0.02)	0.08 *** (0.01)	0.07 *** (0.01)	0.02 ** (0.01)
Count model: FORMViolence/Conflict	0.01 (0.06)	0.01 (0.04)	0.05 (0.03)	0.04 (0.02)	-0.01 (0.02)	-0.08 *** (0.01)	-0.09 *** (0.01)	-0.09 *** (0.01)
Count model: FORMLegal/Institution	-0.13 ** (0.05)	-0.10 *** (0.03)	-0.11 *** (0.02)	-0.12 *** (0.02)	-0.16 *** (0.01)	-0.16 *** (0.01)	-0.17 *** (0.01)	-0.15 *** (0.00)
Count model: POP	0.07 *** (0.02)	0.05 *** (0.01)	0.05 *** (0.01)	0.07 *** (0.01)	0.08 *** (0.01)	0.10 *** (0.00)	0.10 *** (0.00)	0.10 *** (0.00)
Count model: SMO	-0.04 ** (0.02)	-0.02 * (0.01)	-0.01 (0.01)	-0.01 (0.01)	0.00 (0.00)	0.01 (0.00)	0.02 *** (0.00)	0.04 *** (0.00)
Count model: POL	-0.06 *** (0.01)	-0.05 *** (0.01)	-0.05 *** (0.01)	-0.06 *** (0.01)	-0.07 *** (0.00)	-0.08 *** (0.00)	-0.09 *** (0.00)	-0.09 *** (0.00)
Count model: VIO	0.25 *** (0.05)	0.19 *** (0.03)	0.17 *** (0.02)	0.19 *** (0.02)	0.21 *** (0.02)	0.19 *** (0.01)	0.13 *** (0.01)	0.12 *** (0.01)
Zero model: (Intercept)	0.39 *** (0.08)	0.16 * (0.06)	-0.07 (0.06)	-0.31 *** (0.06)	-0.66 *** (0.06)	-1.15 *** (0.06)	-1.78 *** (0.07)	-2.35 *** (0.09)
Zero model: DECADE70s	-0.03 (0.05)	-0.05 (0.04)	0.00 (0.04)	0.04 (0.04)	0.04 (0.04)	0.07 (0.04)	0.24 *** (0.05)	0.37 *** (0.06)

(5) Calculate the CIs and DIs

DI is calculated as ratio of the predicted counts, namely, $P_{\text{pre_t}}$ and $P_{\text{post_t}}$ obtained from the model specified in Step 4. The corresponding variance can be approximated using delta method (Papanicolaou 2009; Xu and Long 2005). For example, we have

$$E(DI_t) \approx \frac{\hat{P}_{\text{post_t}}}{\hat{P}_{\text{pre_t}}} \text{ and}$$

$$\begin{aligned} \text{var}(DI_t) &\approx \frac{1}{\hat{P}_{\text{pre_t}}^2} \text{var}(\hat{P}_{\text{post_t}}) + \frac{\hat{P}_{\text{post_t}}^2}{\hat{P}_{\text{pre_t}}^4} \text{var}(\hat{P}_{\text{post_t}}) - \frac{\hat{P}_{\text{post_t}}}{\hat{P}_{\text{pre_t}}^3} \text{cov}(\hat{P}_{\text{post_t}}, \hat{P}_{\text{pre_t}}) \\ &= \left(\frac{\hat{P}_{\text{post_t}}}{\hat{P}_{\text{pre_t}}} \right)^2 \left(\frac{\text{var}(\hat{P}_{\text{post_t}})}{\hat{P}_{\text{post_t}}^2} + \frac{\text{var}(\hat{P}_{\text{pre_t}})}{\hat{P}_{\text{pre_t}}^2} - 2 \frac{\text{cov}(\hat{P}_{\text{post_t}}, \hat{P}_{\text{pre_t}})}{\hat{P}_{\text{post_t}} \times \hat{P}_{\text{pre_t}}} \right). \end{aligned}$$

If we further assume $P_{\text{pre_t}}$ and $P_{\text{post_t}}$ are independent, then it yields

$$\text{var}(DI_t) \approx \left(\frac{\hat{P}_{\text{post_t}}}{\hat{P}_{\text{pre_t}}} \right)^2 \left(\frac{\text{var}(\hat{P}_{\text{post_t}})}{\hat{P}_{\text{post_t}}^2} + \frac{\text{var}(\hat{P}_{\text{pre_t}})}{\hat{P}_{\text{pre_t}}^2} \right).$$

```
y1 = ggeffects::ggpredict(n1, terms = j, type = 'zero_inflated'  
y2 = ggeffects::ggpredict(n2, terms = j, type = 'zero_inflated'
```

```
PRE = y1$predicted
```

```
POST = y2$predicted
```

```
fit = log(y2$predicted/y1$predicted)
```

```
ratio = exp(fit)
```

```
cov1<-vcov(n1)[1:ncol(x1),1:ncol(x1)]
```

```
cov2<-vcov(n2)[1:ncol(x2),1:ncol(x2)]
```

```
v.d = x1%*%cov1%*%t(x1)+x2%*%cov2%*%t(x2)
```

```
se = sqrt(diag(v.d))
```

```
upper = exp(fit + 1.96*se)
```

```
lower = exp(fit - 1.96*se)
```

A Five-Step Method to Measure Diffusion

- (1) Use event-based data (protests as cases, with key information such as time/location and other features)
 - (2) Define the temporal (T) and spatial/geographical ranges (S);
 - (3) For each observation, count the numbers of events (N) that occurred before and after the selected observation within the defined temporal and spatial ranges;
 - (4) Predict the counts (P) with appropriate models;
 - (5) Calculate the ratios of predicted values (P) from post-event and pre-event count models for corresponding predictors, which are the risk factors; use delta method to generate the CI of the ratio.
- ✓ The ratio will serve as the diffusion indices (DIs) and corresponding Confidence Intervals (CIs) will be calculated as well.

Method

Data, Variables and Modeling

(I) Dynamics of Collective Action (DOCA) data

- DOCA is the most widely used social movement data in American sociology of contentious politics (publications in ASR, AJS, ARS, SF, SMS, Mobilization...)
- DOCA records more than 23,000 protests that took place during 1960-1995, in the USA.
- DOCA's information source is New York Times' reports on the contentious incidents.
- DOCA records the following variables:
 - Time / Location – the key information to measure diffusion
 - Size, Form of Action, Population composition, Social Movement Organizations involved, Policing and Violence

Party Affiliation Data

- Online Scraping (Wikipedia) + Data Cleaning
- All presidents, governors from 1960/01/01 – 1995/12/31.

State	Code	List of governors	Count	Name	Party	Year	1	12	1991	1	14
Oklahoma	OK	List of governors of Oklahoma	23	Henry Bellmon(1921?2009)	Republican	1987	1	12	1991	1	14
Oklahoma	OK	List of governors of Oklahoma	24	David Walters(b. 1951)	Democratic	1991	1	14	1995	1	09
Oklahoma	OK	List of governors of Oklahoma	25	Frank Keating(b. 1944)	Republican	1995	1	09	2003	1	13
Oregon	OR	List of governors of Oregon	29	Mark Hatfield	Republican	1959	1	12	1967	1	09
Oregon	OR	List of governors of Oregon	30	Tom McCall	Republican	1967	1	09	1975	1	13
Oregon	OR	List of governors of Oregon	31	Robert W. Straub	Democratic	1975	1	13	1979	1	08
Oregon	OR	List of governors of Oregon	32	Victor Atiyeh	Republican	1979	1	08	1987	1	12
Oregon	OR	List of governors of Oregon	33	Neil Goldschmidt	Democratic	1987	1	12	1991	1	14
Oregon	OR	List of governors of Oregon	34	Barbara Roberts	Democratic	1991	1	14	1995	1	09
Oregon	OR	List of governors of Oregon	35	John Kitzhaber	Democratic	1995	1	09	2003	1	13
Pennsylva	PA	List of governors of Pennsylvania	37	David L. Lawrence	Democratic	1959	1	20	1963	1	15
Pennsylva	PA	List of governors of Pennsylvania	38	William Scranton	Republican	1963	1	15	1967	1	17
Pennsylva	PA	List of governors of Pennsylvania	39	Ray Shafer	Republican	1967	1	17	1971	1	19
Pennsylva	PA	List of governors of Pennsylvania	40	Milton Shapp	Democratic	1971	1	19	1979	1	16
Pennsylva	PA	List of governors of Pennsylvania	41	Dick Thornburgh	Republican	1979	1	16	1987	1	20
Pennsylva	PA	List of governors of Pennsylvania	42	Bob Casey Sr.	Democratic	1987	1	20	1995	1	17
Pennsylva	PA	List of governors of Pennsylvania	43	Tom Ridge	Republican	1995	1	17	2001	10	05
Rhode Isl&	RI	List of governors of Rhode Island	64	Christopher Del Sesto	Republican	1959	1	06	1961	1	03
Rhode Isl&	RI	List of governors of Rhode Island	65	John A. Notte, Jr.	Democratic	1961	1	03	1963	1	01
Rhode Isl&	RI	List of governors of Rhode Island	66	John Chafee	Republican	1963	1	01	1969	1	07
Rhode Isl&	RI	List of governors of Rhode Island	67	Frank Licht	Democratic	1969	1	07	1973	1	02
Rhode Isl&	RI	List of governors of Rhode Island	68	Philip W. Noel	Democratic	1973	1	02	1977	1	04
Rhode Isl&	RI	List of governors of Rhode Island	69	J. Joseph Garrahy	Democratic	1977	1	04	1985	1	01
Rhode Isl&	RI	List of governors of Rhode Island	70	Edward D. DiPrete	Republican	1985	1	01	1991	1	01
Rhode Isl&	RI	List of governors of Rhode Island	71	Bruce Sundlun	Democratic	1991	1	01	1995	1	03
Rhode Isl&	RI	List of governors of Rhode Island	72	Lincoln Almond	Republican	1995	1	03	2003	1	07
South Car	SC	List of governors of South Carolina	106	Ernest Hollings	Democratic	1959	1	20	1963	1	15

Variables

- Basics
 - Date (to count cases within certain **t** days)
 - Location (State information was used to count cases)
- Risk Factors
 - Size of protest (1-9, 10-49, 50-99, 100-999, 1000-9999, 10000+)
 - Form of action (strikes, rallies, ceremonies, conflicts, legal actions...)
 - SMOs (number of organizations)
 - Policing (DUMMY: whether policing happens?)
 - Violence (DUMMY: whether violence happens?)
 - President/Governor's Party (Republican vs. Democratic)

ZIP Models

- Study 1: Decade (control) + Size, Form of Action, SMO, Violence
- Study 2: Decade + President's Party * Governor's Party
- Study 3: Decade + Governor's Party * Policing.

Findings

Study I: Size of Protest, Form of Action

- Size:
 - Less than 10: tend to decay after day 60
 - 10-1000: tend to diffuse from day 1 to day 60
 - *Large protests consume resources; small protests – difficult to maintain*
- Form of action:
 - Dramaturgical / Institutional / Picketing: tend to decay from day 1 to 60
 - Rally / March tend to decay from day 60 – 90
 - Conflict: tend to decay immediately from day 3 to day 7
 - *Resource Mobilization Theory's Perspective – certain protests are signaling (contagious to others); however certain actions are consuming resources and exhausting other people's change to mobilize.*

Fig.1(A) Number of Participants

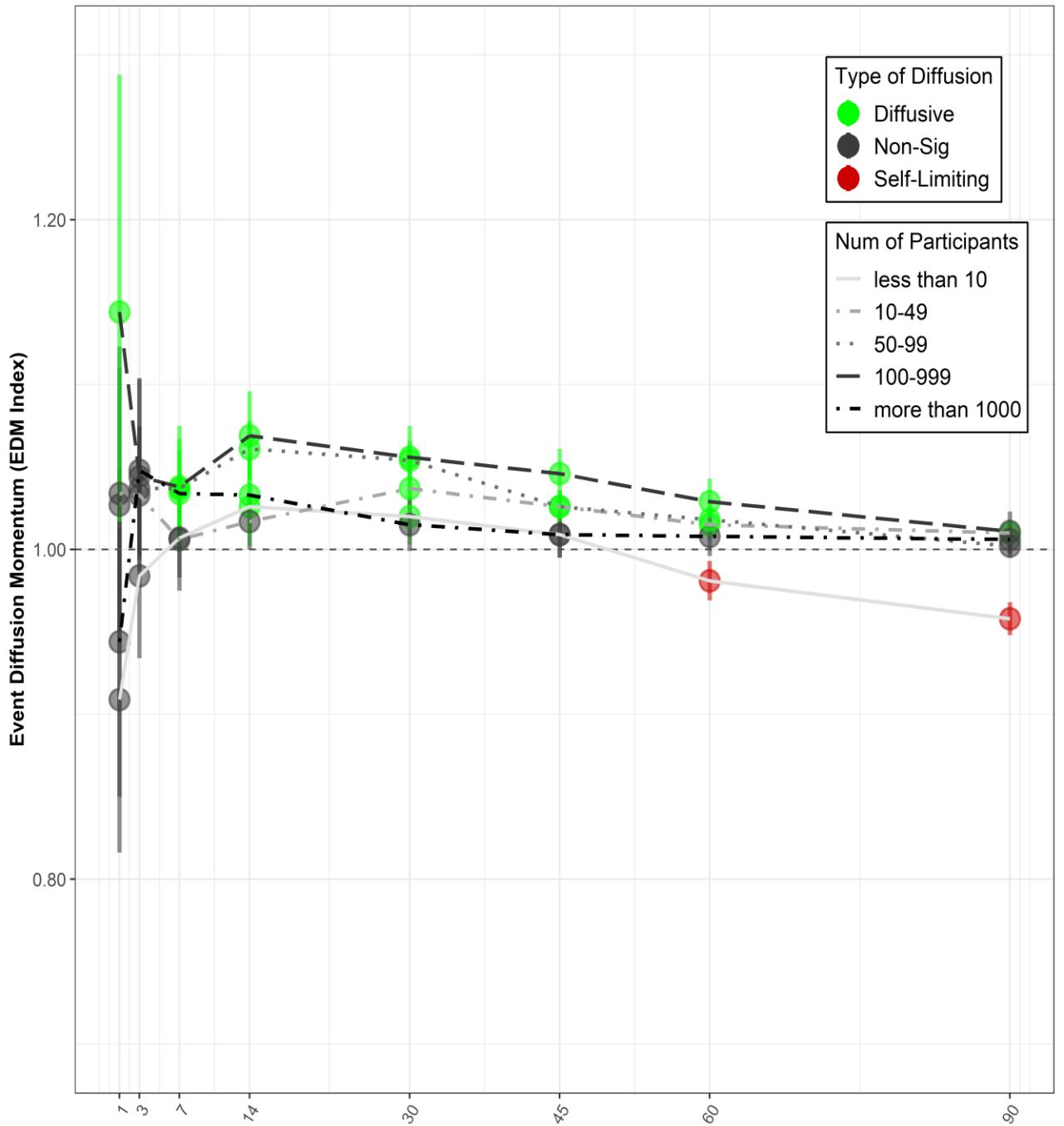
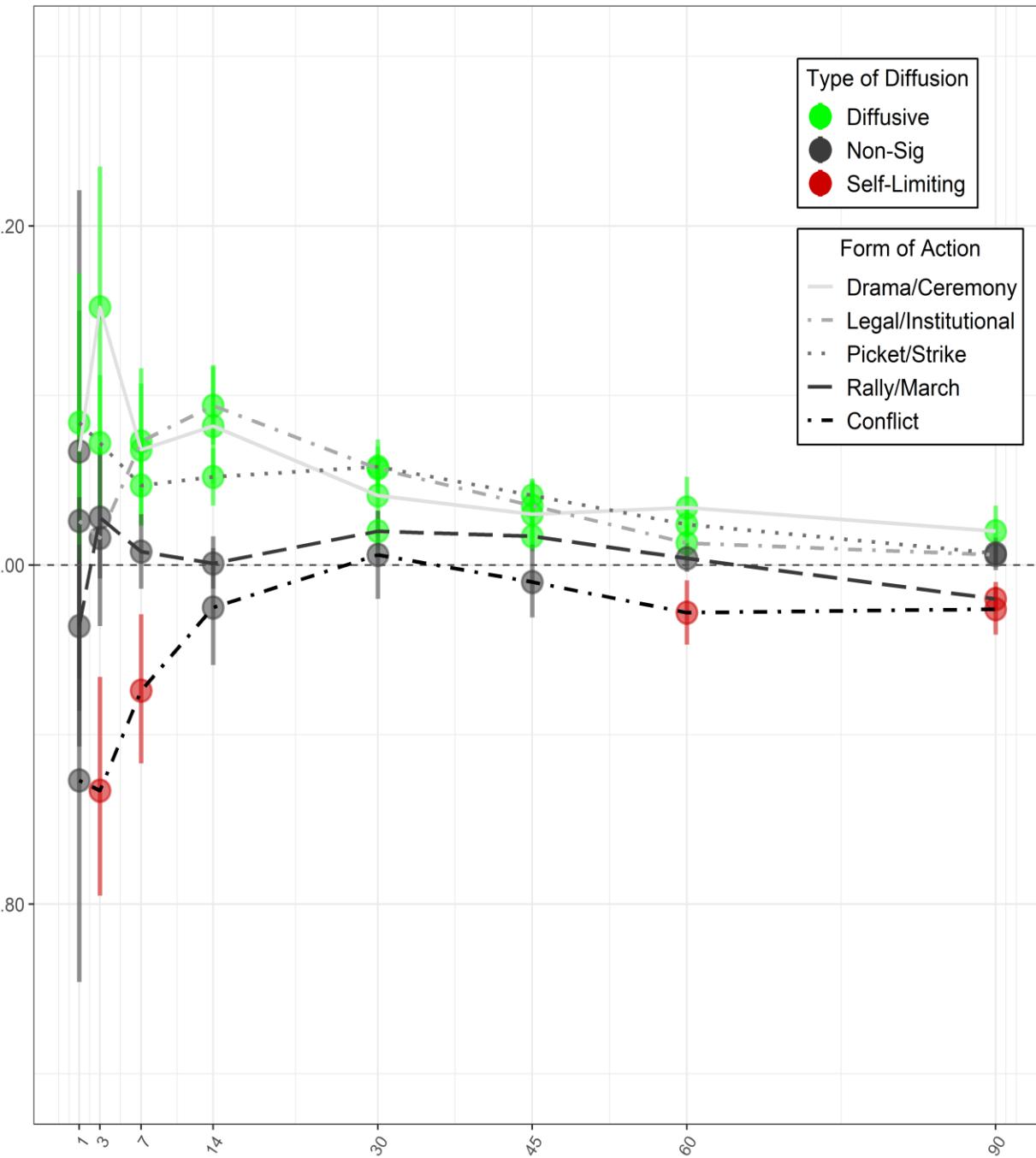


Fig.1(B) Form of Action



Study I: SMOs & Violence

- SMOs
 - No SMO – decay after day 90
 - One SMO – diffusive: day 14-45
 - Multi-SMOs – diffusive: day 3-60
 - *Organized actions are more likely to maintain and diffuse.*
- Violence
 - Violent cases are diffusive (day 3-60)
 - Non violent cases are self-limiting (day 3-45)
 - *Violence has the power of provoking emotions (sadness, anger, sympathy)*

Fig.1(C) Number of SMOs involved

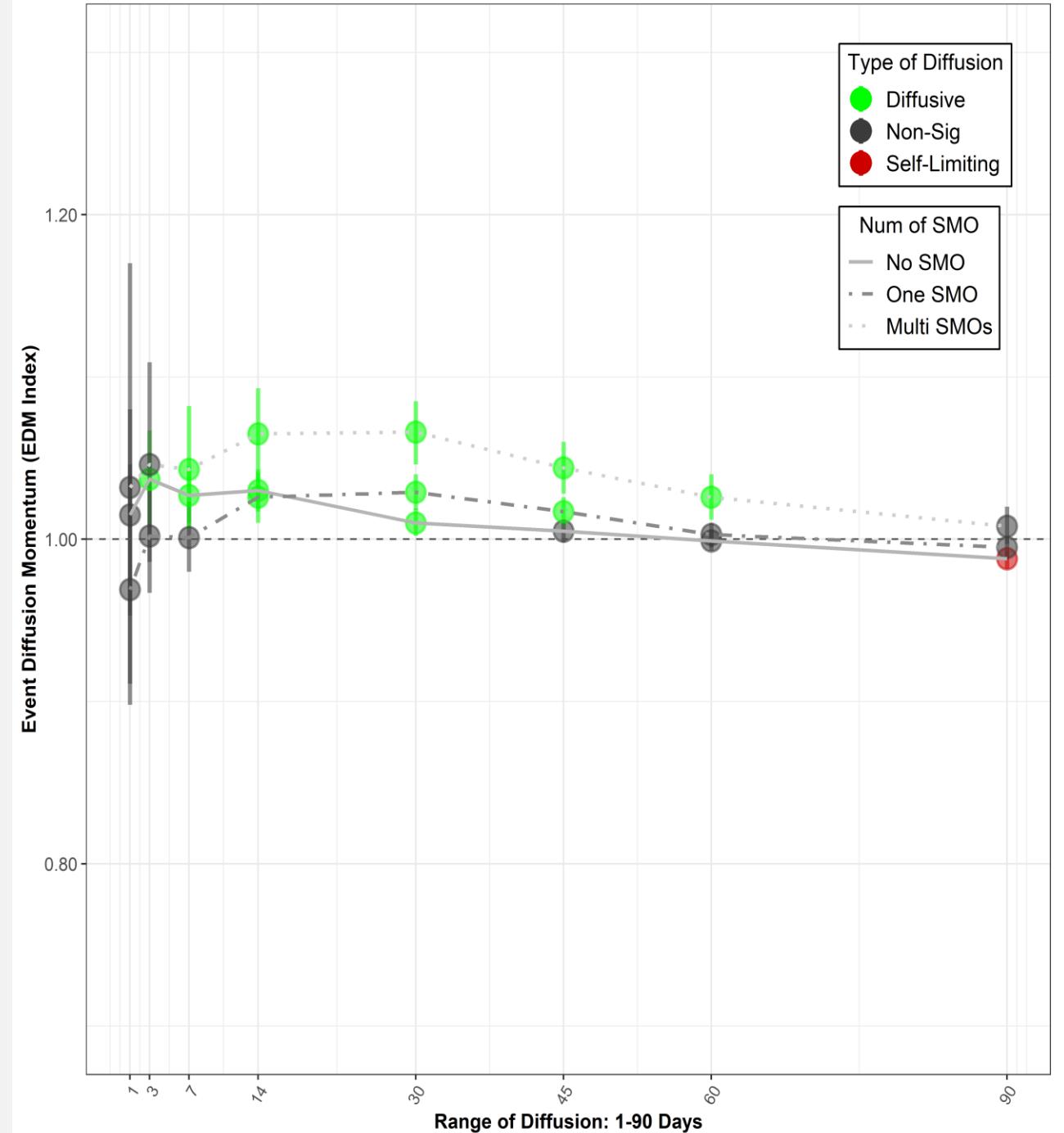
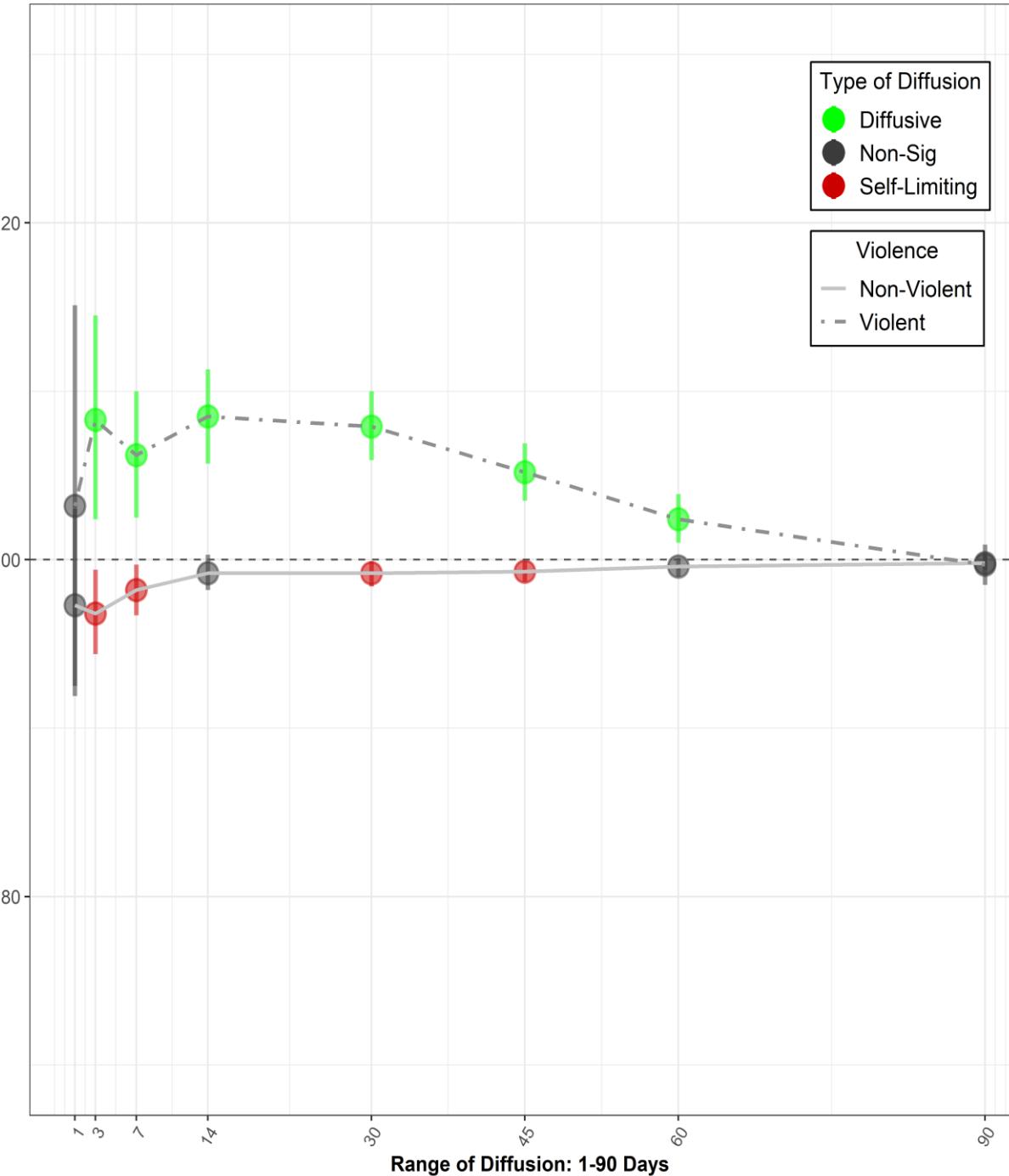


Fig.1(D) Violent vs. Non-Violent Protests



Study 2: POTUS & Gov't Party Affiliation

- Democratic POTUS
 - x Democratic Governor (decay after day 90)
 - x Republican Governor (diffuse after day 60)
- Republican POTUS
 - x Democratic Governor (neutral)
 - x Republican Governor (decay after day 45)
- Same party leads to decay; across-party (D-R) leads to diffuse
- “党同伐异”

Fig.2(A) EDM under Democratic Presidents

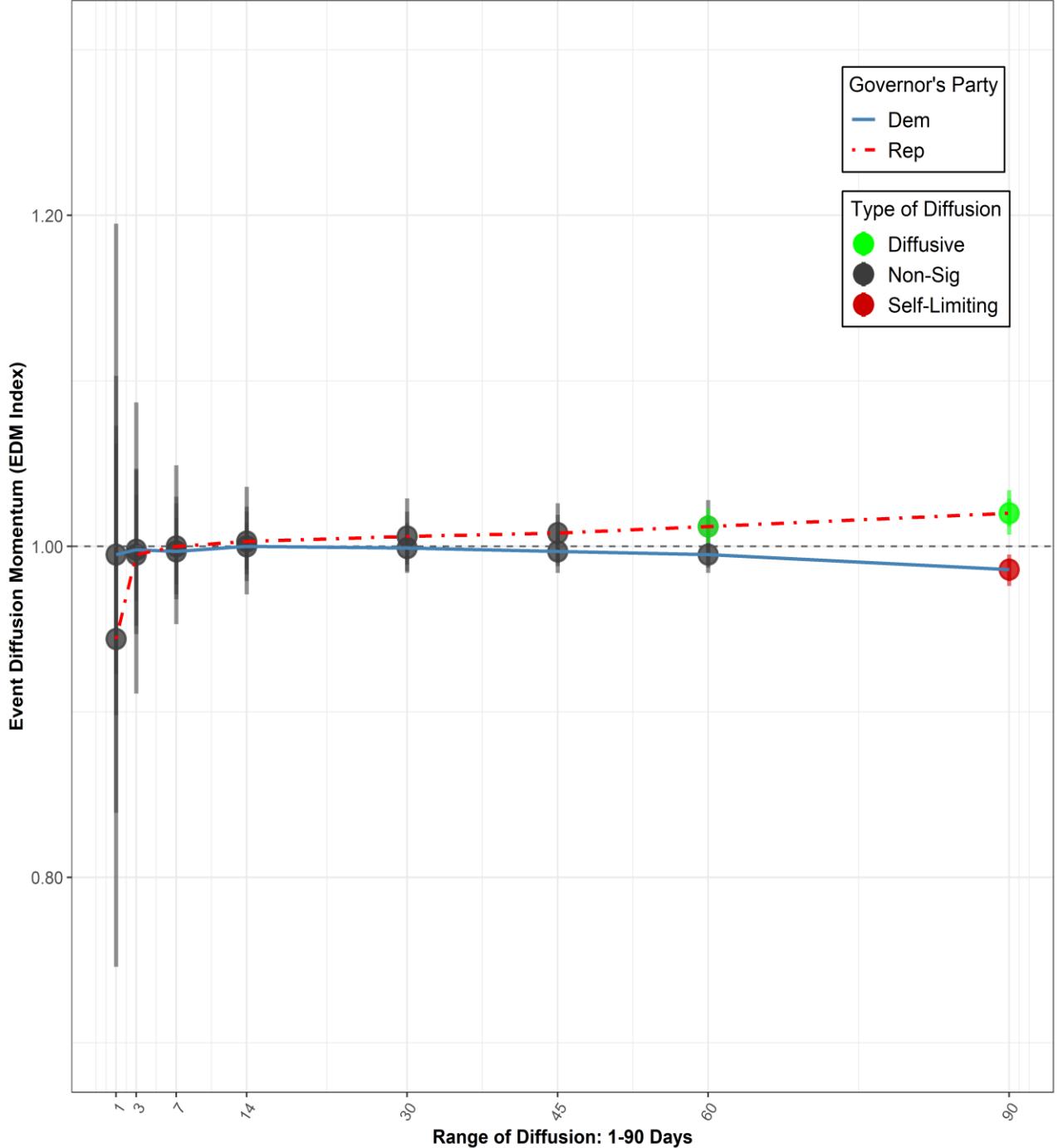
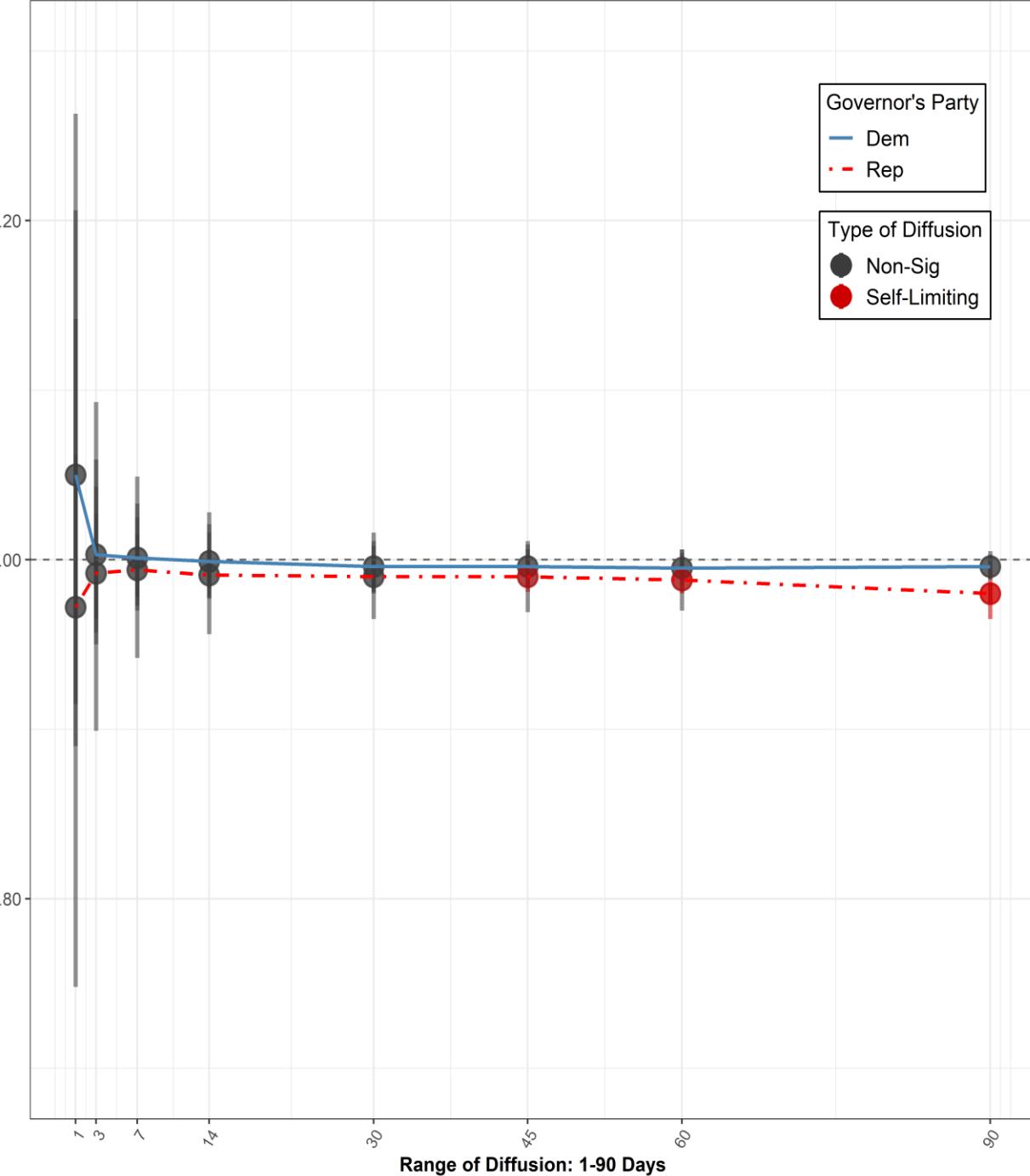


Fig.2(B) EDM under Republican Presidents



Study 3: Gov't Party Affiliation & Policing

- Democratic Governor
 - x No Policing (decay after day 90)
 - x Policing (no effect)
 - “Blue states” – fewer guns, more urban/educated population?
- Republican Governor
 - x No Policing (decay day 30-45)
 - x Policing (diffuse day 30-45)
 - Maybe this is due to features of “Red States” (more guns, more armed conflicts, more risks/likely to engage in conflicts)

Fig.3(A) EDM under Democratic Governors

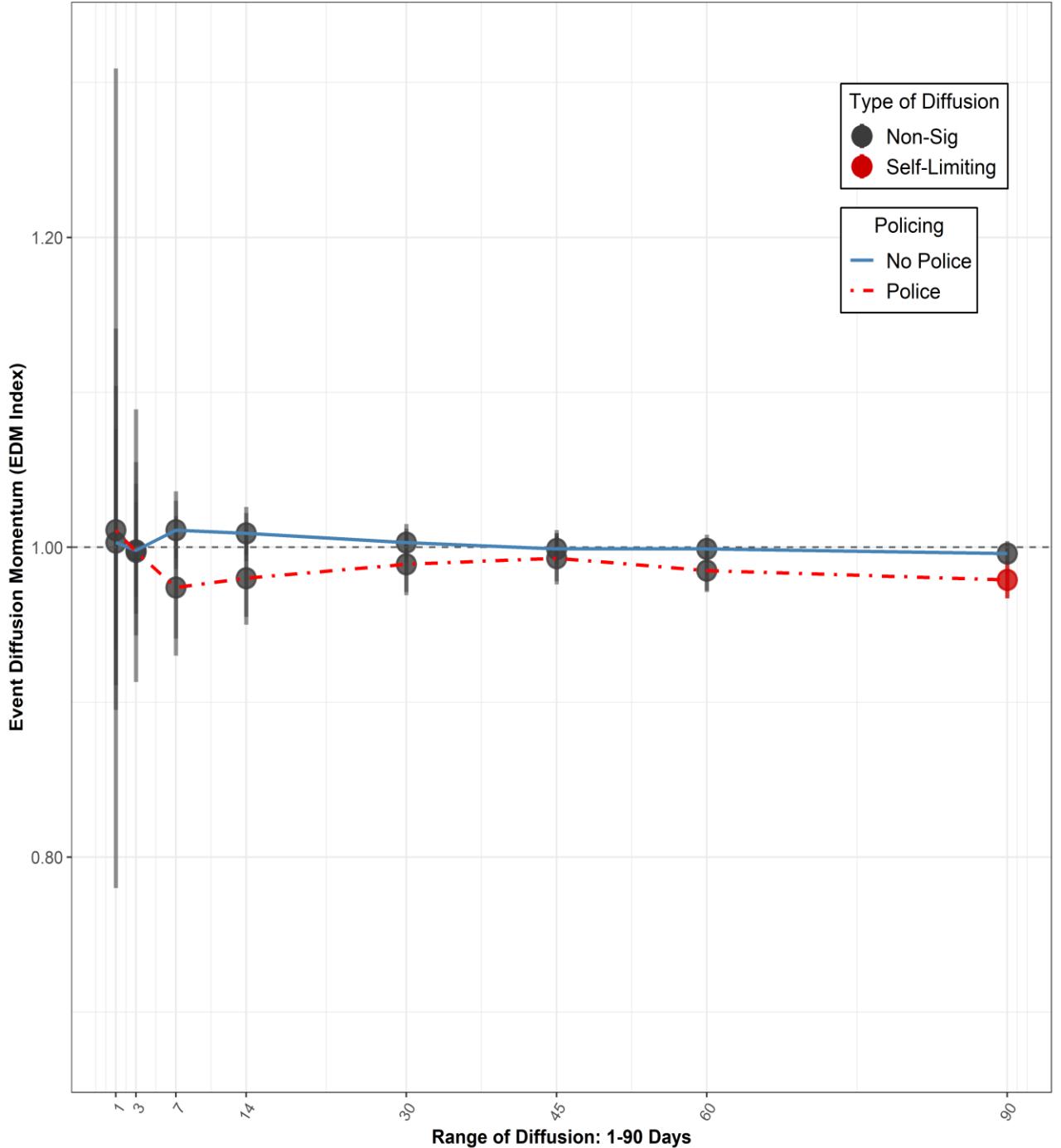
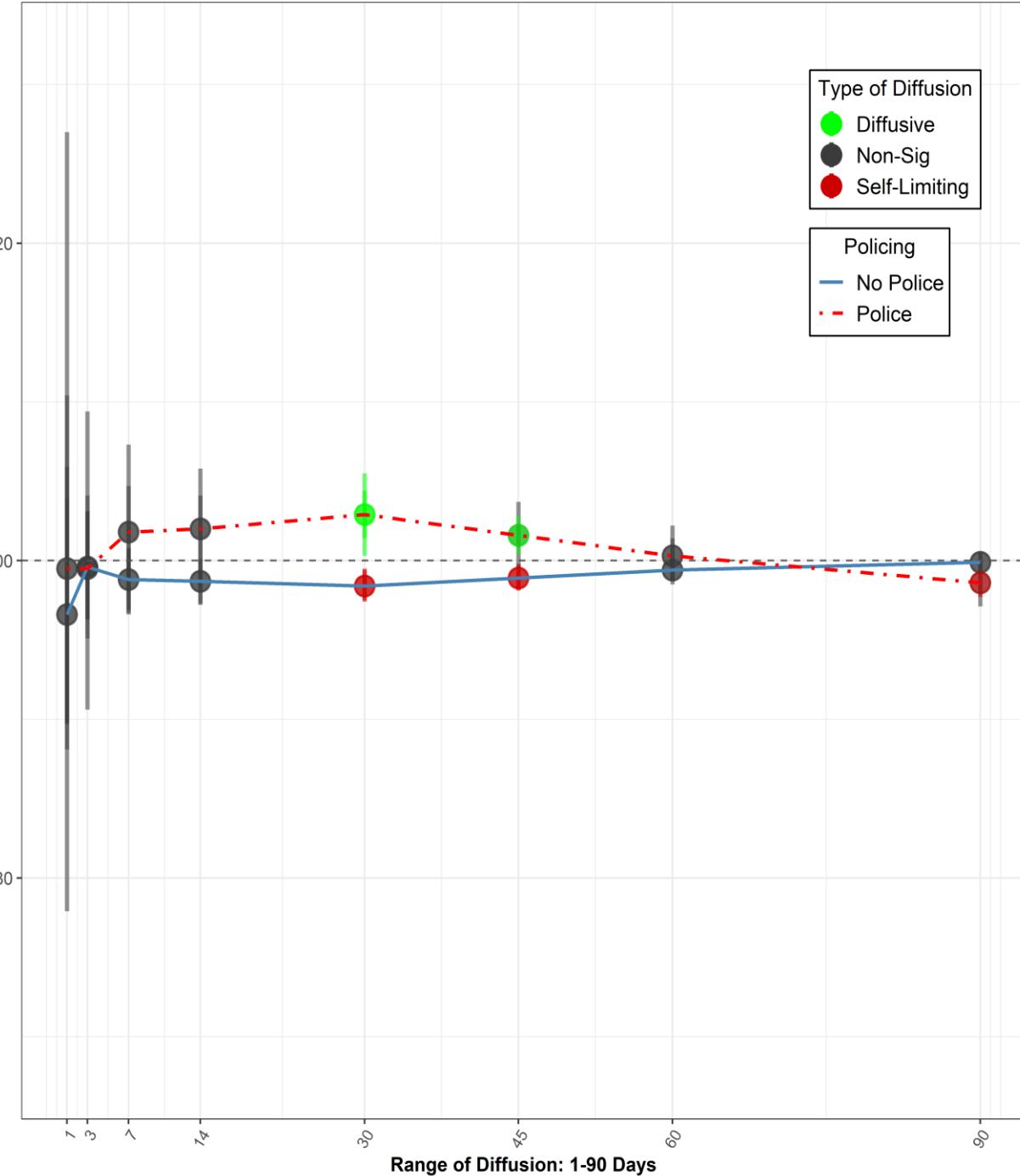


Fig.3(B) EDM under Republican Governors



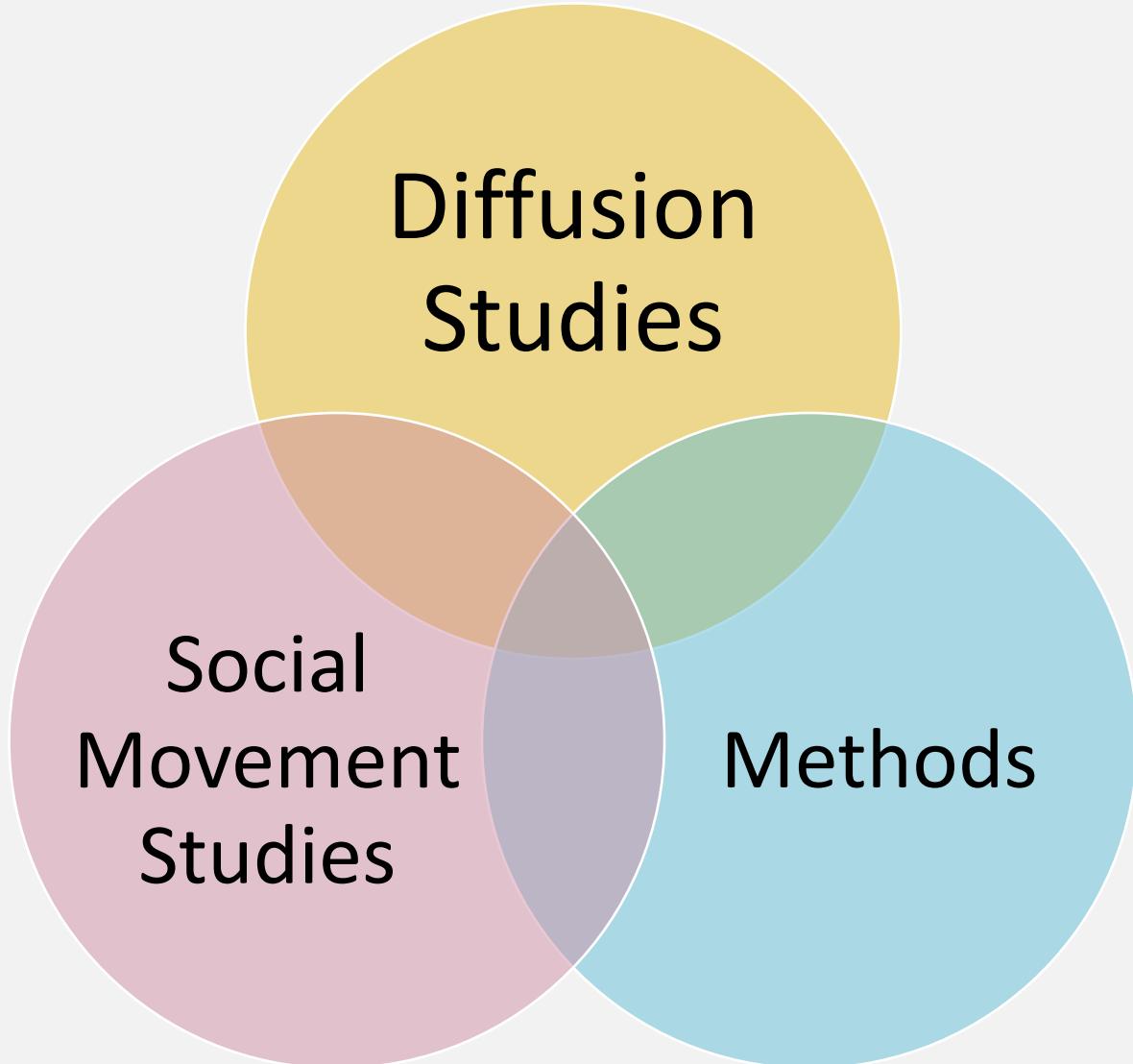
A Summary of Findings

- **Study 1**
 - Mid-sized protests tend to diffuse.
 - Symbolic actions tend to diffuse.
 - Protests that consume a lot of social resources tend to decay
 - *Large rallies tend to decay; legal, institutional ac*
 - Organized protests tend to diffuse.
 - Violent protests tend to diffuse.
- **Study 2**
 - Same party leads to decay; opponent parties lead to diffuse.
- **Study 3**
 - Republican states – policing leads to diffuse, non-policing leads to decay

Discussion and Conclusion

Contributions

- Social Movement Studies / Theoretical & Empirical
 - Identified a few risk factors of protest diffusion, which benefit social movement studies (political opportunity theory, resource mobilization theory)
- Diffusion Studies / Theoretical & Methodological
 - Turning to an inter-event approach and focusing on event's features
 - An approach for understanding non-cumulative events' diffusion
- Methods
 - A five-step method to calculate event diffusion momentum (EDM)
 - Objective, standardized, systematic, avoid researcher's bias
 - Generalizability – can be applied to data with similar structure – events data with temporal/spatial information.



Limitations and Future Agenda

- Protests were assigned equal weights – shall we see them differently?
 - Can we assume all events have the same impacts in reality and same weights in calculation?
- Long-term social changes – the context of diffusion changed.
 - From Eisenhower to Bill Clinton – can we assume contextual homogeneity? Maybe not.
- A geographical-spatial perspective could be incorporated in the future.
 - State border has its strengths; but what about physical space/distance?
- Data quality
 - Problems of news paper data (Earl et al. 2004 - ARS)
 - Needs more unbiased, comprehensive data - calling for automated generation of big data (Hanna 2017)

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THANKS!

How this project evolves...

- 2016 Idea emerged.
- 2017 Finish programming & analysis.
- 2018 First draft completed.
- 2019 Rejected by a top journal.
- 2020 Redo after discussing with Dr. Cai; another submission & reject by 2 top journals in SOC and POLI-SCI.
- 2021 Submit again (under review at another top-tier journal).
- 2022 Hopefully...

Interesting Issues

- Looping & Vectorized Calculation in R
 - GitHub / StackOverflow Community
- Effects & Matrix Extraction with R
 - “effects” package 2018
 - “margins” package 2019
 - “ggeffects” package 2020
 - “emmeans” package 2021