Diffusion of Social Movements: Toward an Inter-Movement Approach

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Outline

- Intro - *Diffusion studies in General*
- Context - *Social Movement Studies about Protest Diffusion*
- Research Design - *A 5-step Method to Generate Diffusion Index*
- Method - *Data,Variables and ZIP Models*
- Findings - *Size, Populations, SMOs, Policing and Violence*
- Discussion - *Implications and Future Agenda*

Diffusion Studies

- Diffusion has been an important topic in many disciplines.
- Epidemiology and Public Health
- Social Sciences
  - Language, Writing Systems, Symbols, Numbers and Notations…
  - Tales, Religion, and Ideology...
  - Technology and Innovations…
  - Financial and Business Models, Organizations, Management Practices…
  - Policies, Institutions and Laws...
  - Criminology…

Social Movements and Diffusion

- It is agreed that social movements diffuse.
  - The protests themselves diffuse;
  - Elements of protests, such as repertoire, strategy, framing and ideology, networks and organizations, personnel and resources, diffuse as well.
- However, there are some gaps in existing studies of protest diffusion.
  - 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.
  - There has not been a widely accepted methodological practice in the field.

We suggest…

- Turning to the inter-movement dynamics of diffusion.
  - "toward an eventful sociology" (Sewell 1996)
- Borrowing wisdom from public health and criminology.
  - E.g. copy-cat crimes, broken window theory. – why and how events lead to similar event?
- Focusing on features of each event, and how they affect diffusion.
  - E.g. what kinds of patients/viruses are more contagious?
  - E.g. what kinds of protests are more diffusive?

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 and geographical ranges;
- ❑ (3) For each observation, count the numbers of events that occurred before and after the selected observation within the defined temporal and spatial ranges;
- ❑ (4) Predict the counts with appropriate models;
- ❑ (5) Calculate the ratios of predicted values from post-event and pre-event count models for corresponding predictors, which are the risk factors.

✓ <u>The calculated ratio will serve as the diffusion indices (DIs) and corresponding Confidence Intervals (CIs) will be calculated as well.</u>

Data, Variables and Modeling

(1) Dynamics of Collective Action (DOCA) data

- DOCA is the most widely used social movement data in American sociology of contentious politics.
- DOCA records more than 23,000 protests that took place during 1960-1995, in the United States.
- DOCA's information source is New York Times' reports on the contentious incidents.

- It 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

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…)
  - Population Composition (how many demographic groups?)
  - SMOs (number of organizations)
  - Policing (DUMMY: whether policing happens?)
  - Violence (DUMMY: whether violence happens?)

(2) Define the Spatial/Temporal Ranges

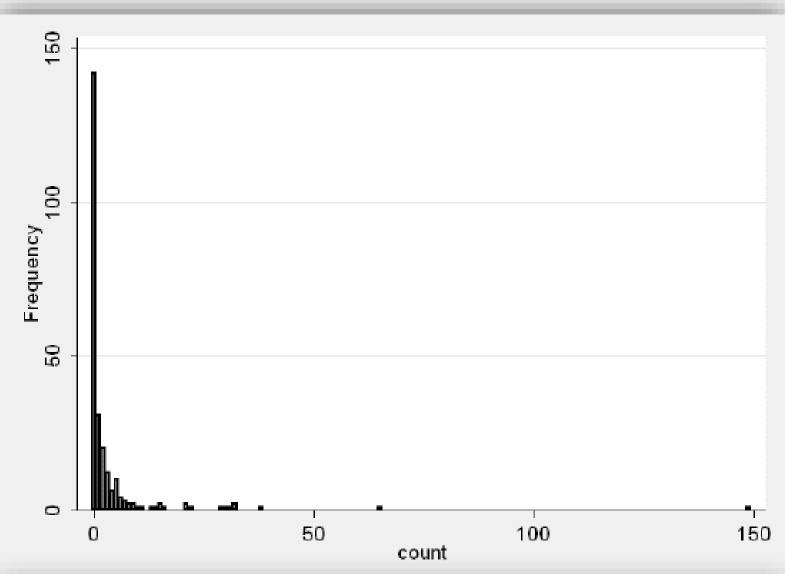
- Spatial
  - Geographic distance?
  - Within the same state. Why?
- Temporal
  - T = 1, 2, 3, 4, 7, 14, 30, and 60 days
  - March 1, 1960 – October 31, 1995

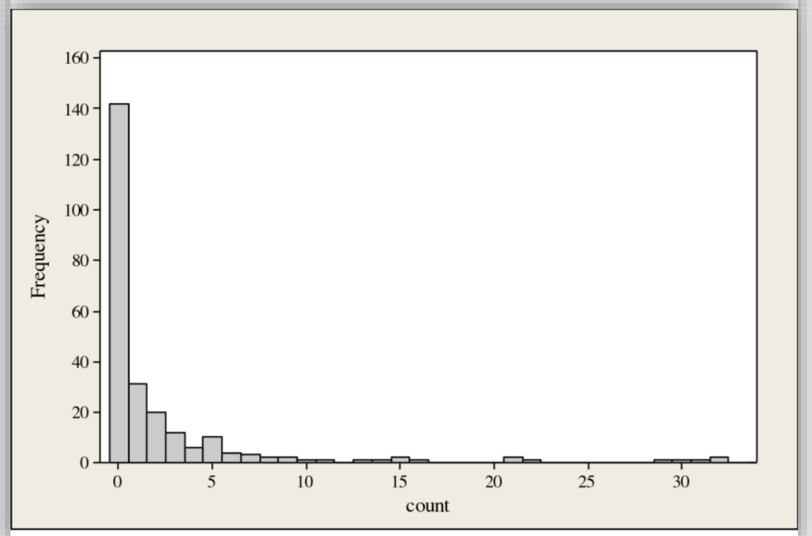
(3) Count the Protests Before/After Each Case

```
> head(event_sub)
       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
> tail(event_sub)
           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?





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

(5) Calculate the CIs and DIs

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

$$E(DI_t) \approx \frac{\hat{P}_{post\_t}}{\hat{P}_{pre\_t}} \;\; and$$

$$var(DI_t) \approx \frac{1}{\hat{P}^2_{pre\_t}} var(\hat{P}_{post\_t}) + \frac{\hat{P}^2_{post\_t}}{\hat{P}^4_{pre\_t}} var(\hat{P}_{post\_t}) - \frac{\hat{P}_{post\_t}}{\hat{P}^3_{pre\_t}} cov(\hat{P}_{post\_t}, \hat{P}_{pre\_t})$$

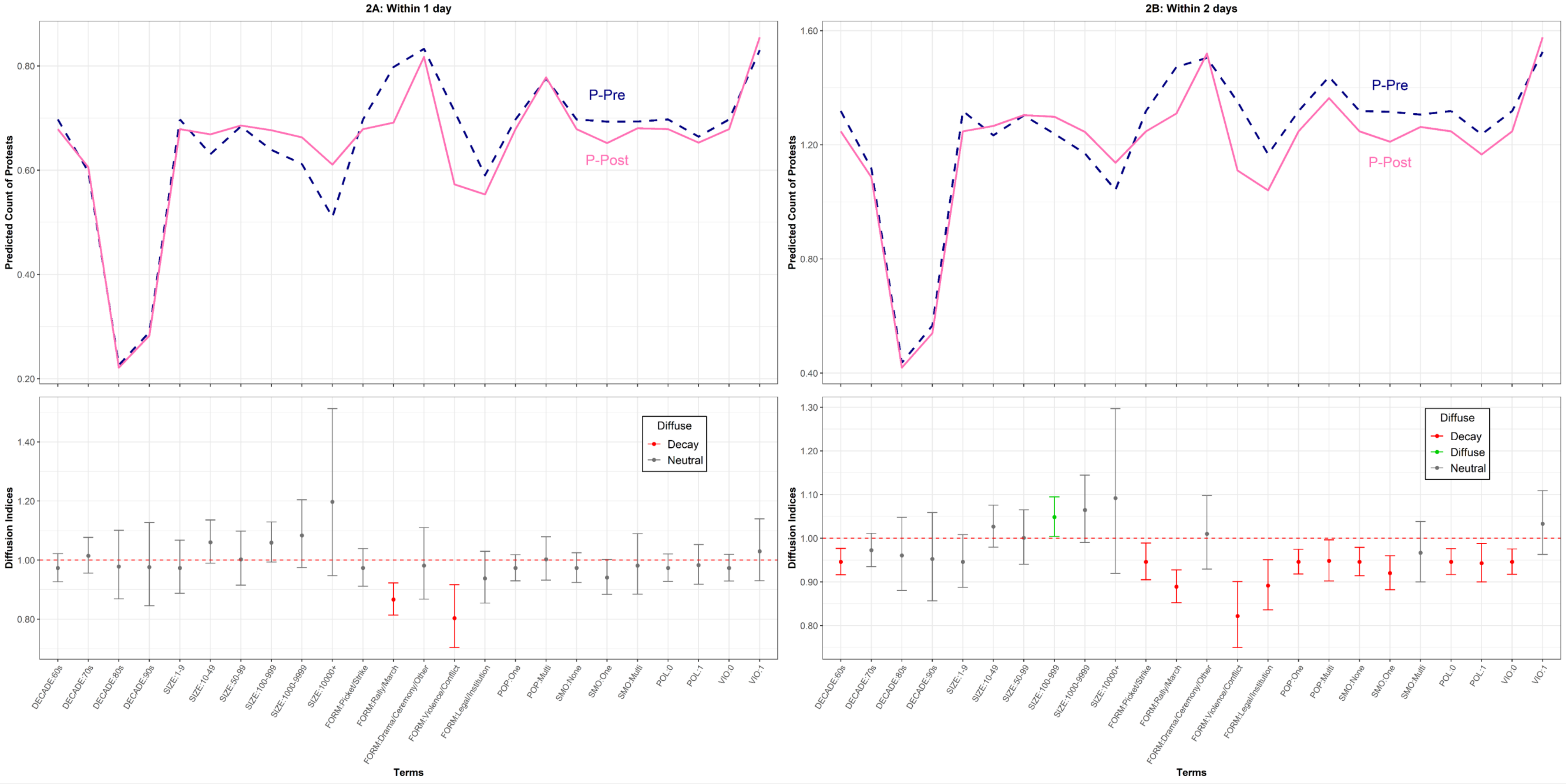
$$= \left(\frac{\hat{P}_{post\_t}}{\hat{P}_{pre\_t}}\right)^2 \left(\frac{var(\hat{P}_{post\_t})}{\hat{P}^2_{post\_t}} + \frac{var(\hat{P}_{pre\_t})}{\hat{P}^2_{pre\_t}} - 2\frac{cov(\hat{P}_{post\_t}, \hat{P}_{pre\_t})}{\hat{P}_{post\_t} \times \hat{P}_{pre\_t}}\right).$$

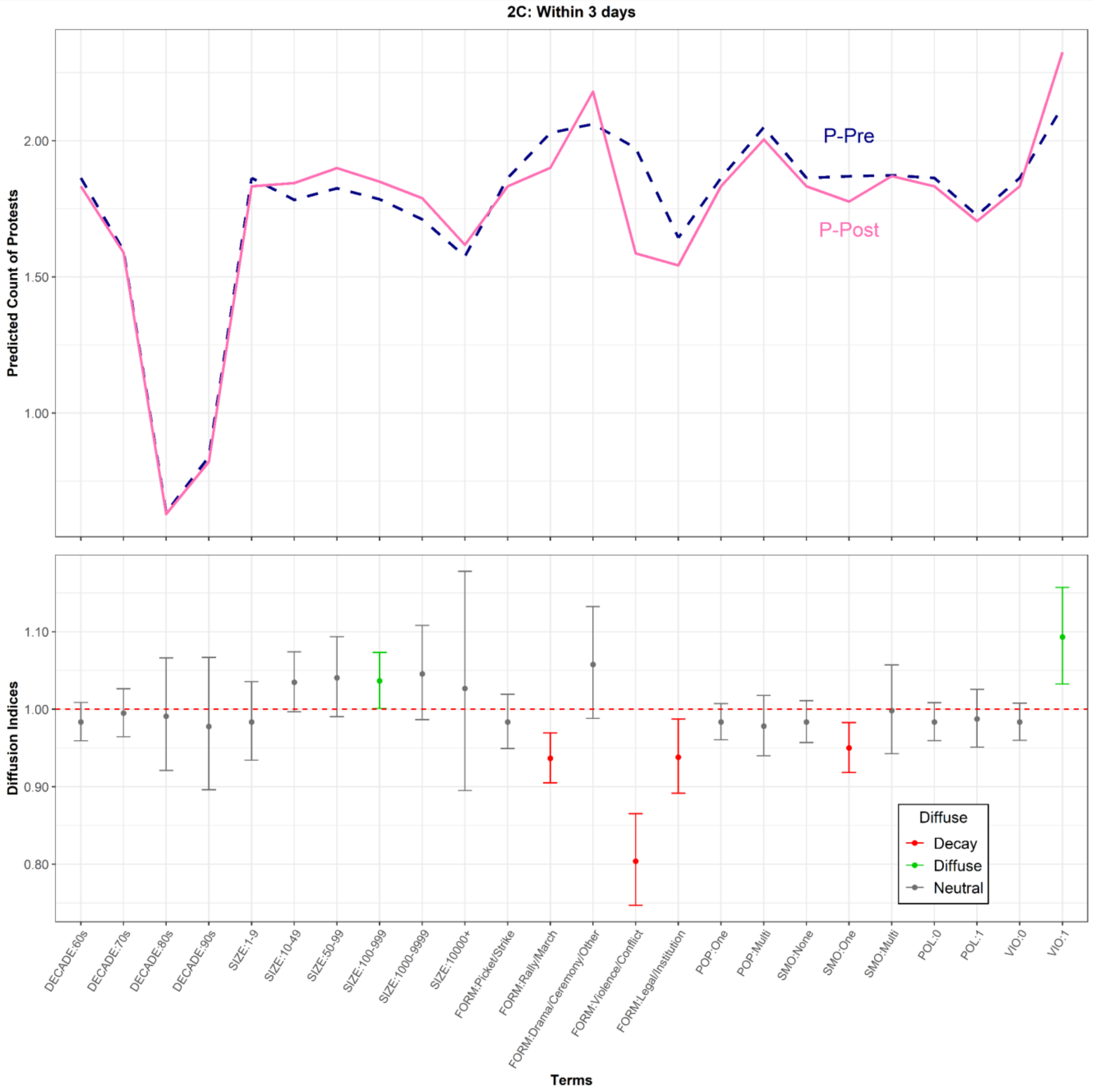
If we further assume $P_{pre\text{-}t}$ and $P_{post\text{-}t}$ are indepdent, then it yields

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

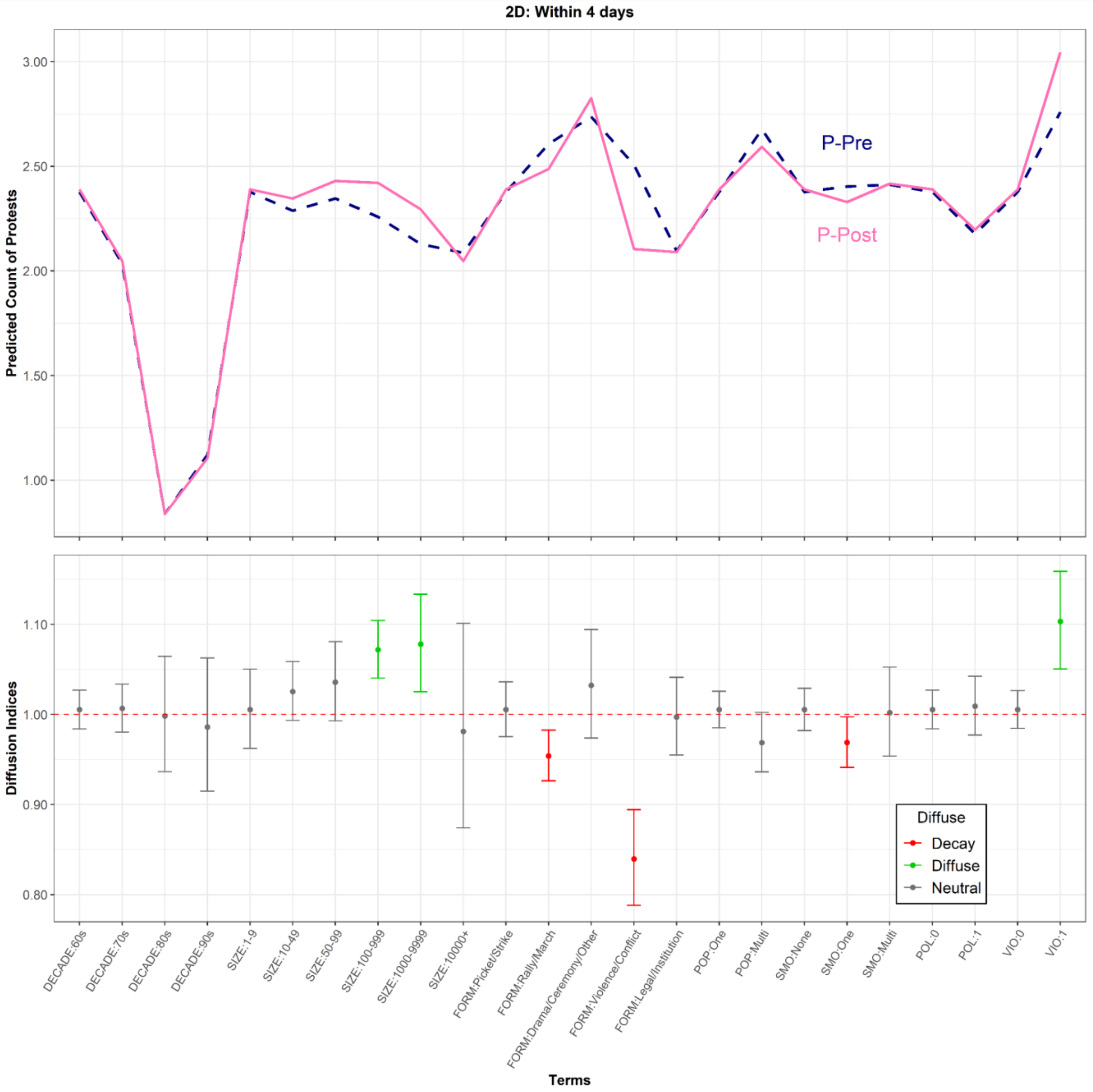
```r
y1 = ggeffects::ggpredict(n1, terms = j, type = 'zero_inflated'
y2 = ggeffects::ggpredict(n2, terms = j, type = 'zero_inflated'

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)
```

Findings

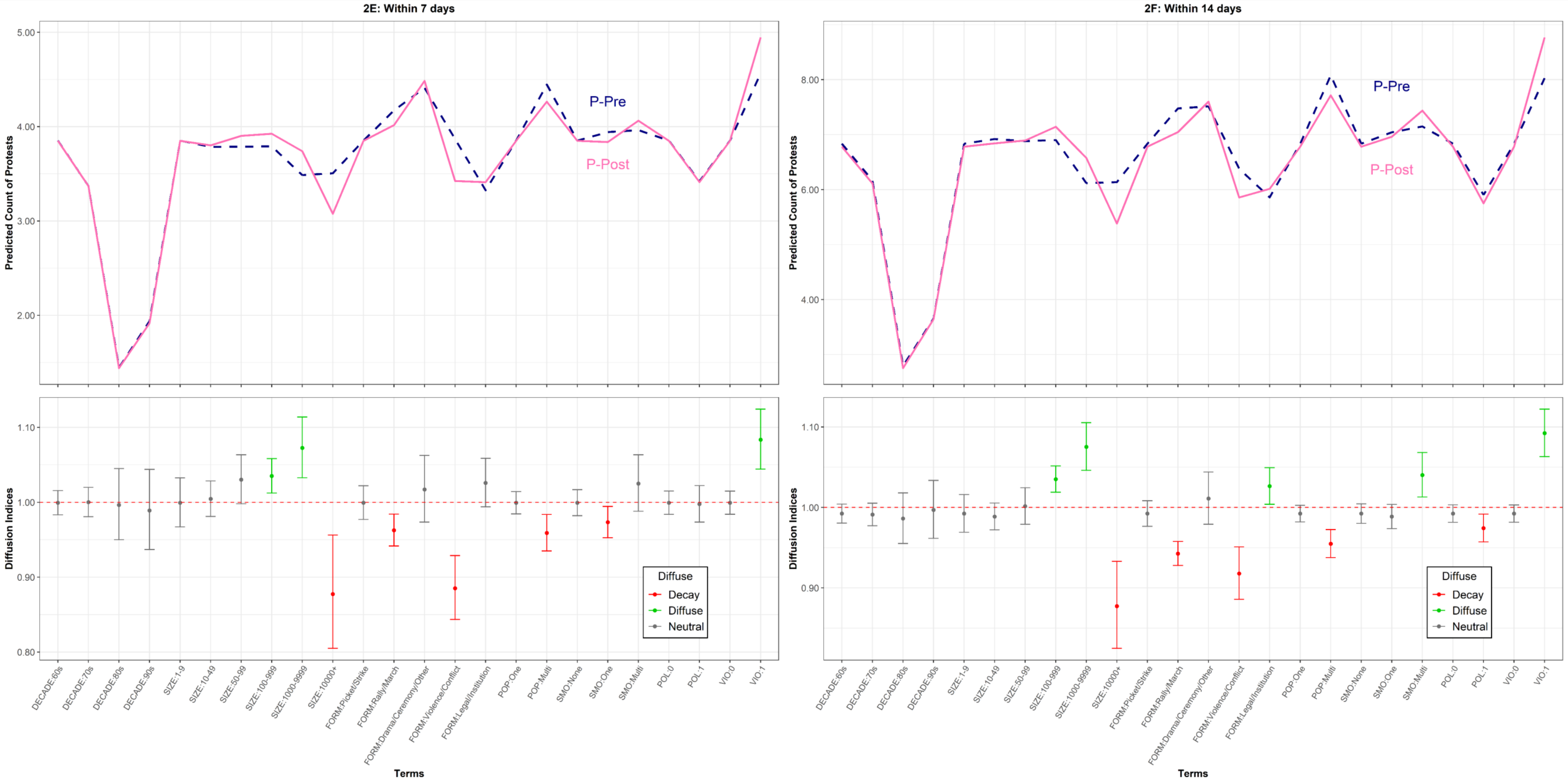

2A: Within 1 day
2B: Within 2 days
Predicted Count of Protests
P-Pre
P-Post
Diffusion Indices
Diffuse
Decay
Diffuse
Neutral
Terms
DECADE:60s
DECADE:70s
DECADE:80s
DECADE:90s
SIZE:1-9
SIZE:10-49
SIZE:50-99
SIZE:100-999
SIZE:1000-9999
SIZE:10000+
FORM:Picket/Strike
FORM:Rally/March
FORM:Drama/Ceremony/Other
FORM:Violence/Conflict
FORM:Legal/Institution
POP:One
POP:Multi
SMO:None
SMO:One
SMO:Multi
POL:0
POL:1
VIO:0
VIO:1



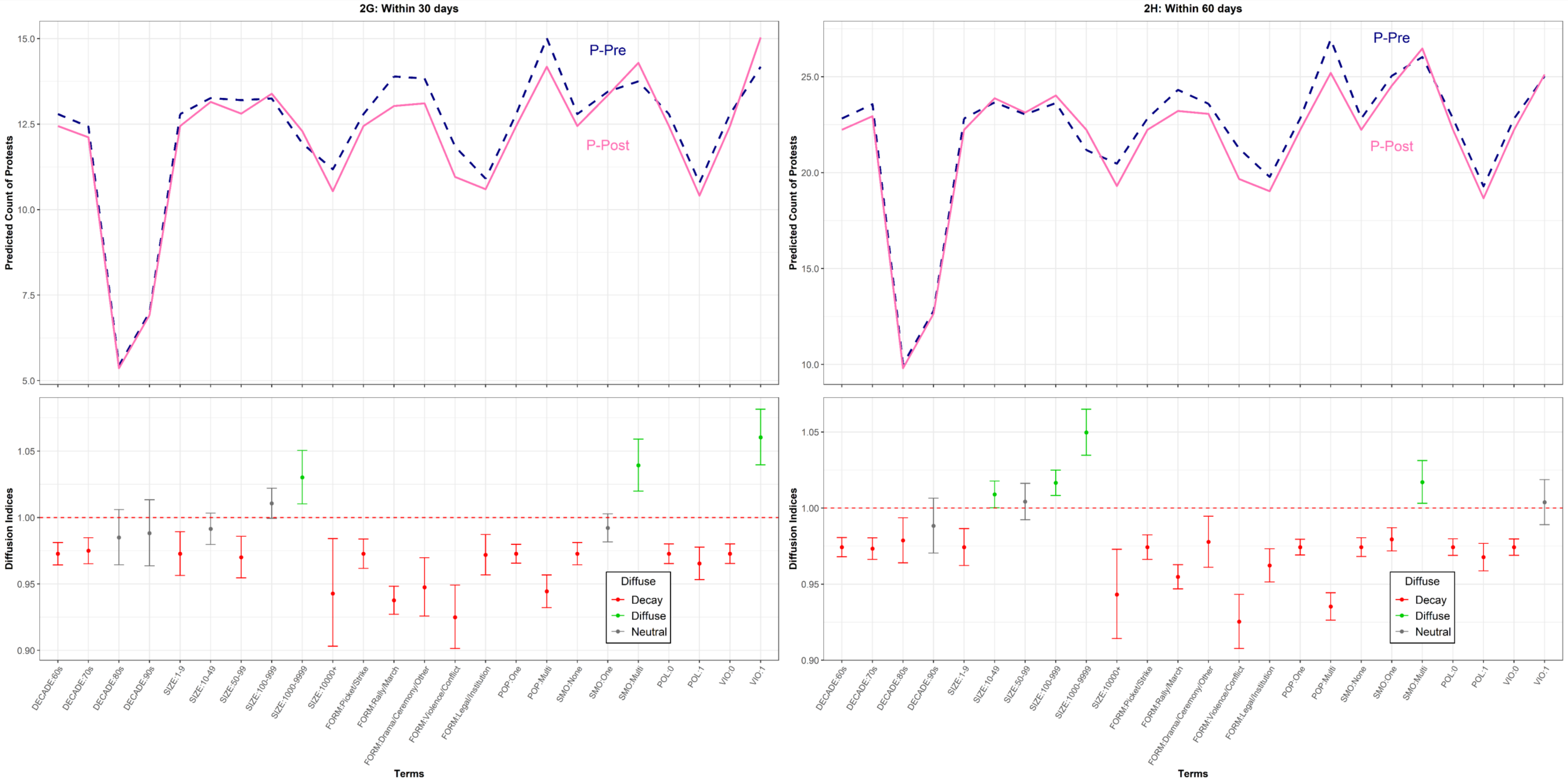
2C: Within 3 days
P-Pre
P-Post
Predicted Count of Protests
Diffusion Indices
Diffuse
Decay
Diffuse
Neutral
DECADE:60s
DECADE:70s
DECADE:80s
DECADE:90s
SIZE:1-9
SIZE:10-49
SIZE:50-99
SIZE:100-999
SIZE:1000-9999
SIZE:10000+
FORM:Picket/Strike
FORM:Rally/March
FORM:Drama/Ceremony/Other
FORM:Violence/Conflict
FORM:Legal/Institution
POP:One
POP:Multi
SMO:None
SMO:One
SMO:Multi
POL:0
POL:1
VIO:0
VIO:1
Terms



2D: Within 4 days
P-Pre
P-Post
Predicted Count of Protests
Diffusion Indices
Diffuse
Decay
Diffuse
Neutral
DECADE:60s
DECADE:70s
DECADE:80s
DECADE:90s
SIZE:1-9
SIZE:10-49
SIZE:50-99
SIZE:100-999
SIZE:1000-9999
SIZE:10000+
FORM:Picket/Strike
FORM:Rally/March
FORM:Drama/Ceremony/Other
FORM:Violence/Conflict
FORM:Legal/Institution
POP:One
POP:Multi
SMO:None
SMO:One
SMO:Multi
POL:0
POL:1
VIO:0
VIO:1
Terms



2E: Within 7 days
2F: Within 14 days
Predicted Count of Protests
P-Pre
P-Post
Diffusion Indices
Diffuse
Decay
Diffuse
Neutral
Terms
DECADE:60s
DECADE:70s
DECADE:80s
DECADE:90s
SIZE:1-9
SIZE:10-49
SIZE:50-99
SIZE:100-999
SIZE:1000-9999
SIZE:10000+
FORM:Picket/Strike
FORM:Rally/March
FORM:Drama/Ceremony/Other
FORM:Violence/Conflict
FORM:Legal/Institution
POP:One
POP:Multi
SMO:None
SMO:One
SMO:Multi
POL:0
POL:1
VIO:0
VIO:1


2G: Within 30 days
2H: Within 60 days
P-Pre
P-Post
Predicted Count of Protests
Diffusion Indices
Diffuse
Decay
Diffuse
Neutral
Terms
DECADE:60s
DECADE:70s
DECADE:80s
DECADE:90s
SIZE:1-9
SIZE:10-49
SIZE:50-99
SIZE:100-999
SIZE:1000-9999
SIZE:10000+
FORM:Picket/Strike
FORM:Rally/March
FORM:Drama/Ceremony/Other
FORM:Violence/Conflict
FORM:Legal/Institution
POP:One
POP:Multi
SMO:None
SMO:One
SMO:Multi
POL:0
POL:1
VIO:0
VIO:1

Main Findings

- Overall, decays are more often than diffusions (due to the general declining trend from 1960s)
- Immediate effects (1-3 days): largely decaying
- Long term effects (7-60 days): mainly decaying, some diffusive
- Size of Protest – inverted U shape curve (midsize diffusive, small/large decaying)
- Forms of Actions – decaying
- SMOs - diffusive
- Violence - diffusive

Discussion and Conclusion

Contributions

- Theoretical
  - Turning to an inter-movement perspective, focusing on events
- Methodological
  - A five-step method to calculate diffusion
  - Objective, standardized, systematic, immune from personal bias
- Empirical
  - Identified a few risk factors of protest diffusion
  - Certain features of social movements are associated with diffusion/decay in a cycle of protest.

Limitations and Future Agenda

- Protests were assigned equal weights – shall we see them differently?

- A geographical-spatial perspective should be incorporated.

- Data quality and limitations – needs more comprehensive data.

- Long-term social changes and how that are reflected in a dynamic diffusion pattern.

THANKS!