Preliminary Draft (2023), , 1–18

RESEARCH NOTE

When France Sneezes, Does Europe Catch Cold? The Dynamics of Temporal and Spatial Diffusion of Political Protests

Valentina González-Rostani and Jeffrey Nonnemacher
Department of Political Science, University of Pittsburgh

Abstract
Are protests contagious throughout time and space? This question has interested scholars of social movements and political behavior for decades but the literature remains divided over whether protests diffuse throughout time and space. Using protest event analysis and by applying novel spatiotemporal autoregressive distributed lag (STADL) models designed to capture both temporal and spatial dependence in the same model, we find significant dependencies across both sources of diffusion. Protests in one time period shape the onset of protests in the future and protests in one country increase protests in a neighboring country. These results contribute further evidence using more rigorous modeling techniques that protests are contagious and have implications for the further study of protest diffusion.

Keywords: Protest, Diffussion, Time-series-cross-section, Spatiotemporal-autoregressive-distributed-lag (STADL) model

1. Introduction

On January 8, 2023, far-right protesters in Brazil stormed the capital, presidential palace, and Supreme Court after claims that the 2022 election was stolen from incumbent President Bolsonaro.[1] The protests drew comparisons to the January 6 insurrection in the US two years prior by Trump supporters.[2] The eerie similarity between the Brazilian and American insurrection two years prior, including how some protesters were dressed, raises questions

1. See "Security forces detain 1,500 after Brasília riots" (BBC, January 9, 2023)
2. See "The attack on Brazil's seat of government resembles the storming of the U.S. Capitol on Jan. 6, 2021" (New York Times, January 8, 2023)

about the contagious nature of political protests and whether we should consider the two events as deeply inter-related or coincidences brought on by similar structural factors. Are protests contagious from country to country and from one year to the next?

Scholars remain divided over whether protests diffuse over time and space. On the one hand, scholars point to the many examples of revolutionary waves as evidence that protests are contagious (Porta 2017; Strauch and Weidmann 2022). On the other hand, some argue that what looks like contagion is actually the presence of similar structural factors that help in the development of protests at similar times (Way 2008; Brancati and Lucardi 2019b). However, in this paper, we argue that the literature has not yet overcome challenges associated with modeling both temporal and spatial dependence at the same time using cross-sectional time series data and analyzes both processes independently of each other (e.g, Box-Steffensmeier et al. 2014; Franzese and Hays 2007, 2008; Strauch and Weidmann 2022). The analysis of temporal or spatial dependence separately can lead to inaccurate conclusions and the misspecification of models. Proper analysis requires accounting for both (Cook, Hays, and Franzese 2022).

To address the limitations posed by the current use of spatial and temporal models on protest diffusion, we employ a novel spatiotemporal autoregressive distributed lag (STADL) model (Cook, Hays, and Franzese 2022) which allows us to examine both temporal and spatial dependence in the same model using cross-sectional time-series data of protest frequency. Through this model, our work makes an important contribution to the literature on protest diffusion and helps abjudicate whether protests are contagious using a novel statistical model that can account for both spatial and temporal dependencies at the same time, reducing the bias in either estimate.

Using protest event analysis (PEA) data that has then been aggregated to the country-level in 26 European countries and the STADL model, we demonstrate that protests do spread throughout time and space. Our findings demonstrate that the number of protests in one country is shaped by the frequency of protests in the year prior and is influenced by the onset of protests in neighboring countries.

This paper is structured as follows. First, we discuss in more depth the state of the literature on the question of protest diffusion and present our argument about why we would expect the diffusion of protests through time and space. Then, we outline our methodological approach and build a STADL model to test our hypotheses. We find evidence for both spatial and temporal diffusion and we conclude by discussing the implications of these findings for the study of protests.

2. Political Protest Across Borders

The spread of protests across countries has received extensive study in the literature on protests and social movements but remains an unsettled question (Brancati and Lucardi 2019a; Porta 2017). Predominantly studied in the context of pro-democracy protests such as the 1989 East Europe movements, Color Revolutions, or the Arab Spring, the literature is generally divided over whether protests spread from one country to another. On the one hand, several studies find limited evidence of diffusion, and conclude that protests do not spread cross-nationally (Brancati and Lucardi 2019b; Bunce and Wolchik 2006; Hale 2019; Kern 2011; Way 2008). They argue that protest diffusion has been overstated, especially in regards to democratic revolutions, and that the emergence of events is best understood from a domestic vantage point. For instance, Way (2008) discounts the "interrelated wave" narrative of the Color Revolutions and identifies similar structural conditions in each country to explain the protests. Similarly, Brancati and Lucardi (2019b) argue that democratic protests do not spread across borders as these are inherently domestic level protests interested in domestic level reforms that do not draw the attention and influence of transnational actors. In short, what appears to be the diffusion of protests from one context to another is actually an artifact of similar domestic factors that all lend themselves to the development of political protests.

On the other hand, there is an extensive literature that finds evidence to suggest that protest diffusion is a real phenomenon (Porta 2017; Gleditsch and Rivera 2017; Lichbach 1985; Keck and Sikkink 2014; Strauch and Weidmann 2022). Importantly, Aidt and Leon-Ablan (2022) find that structural factors and diffusion work in tandem with one another where-in conducive structural factors serve to strengthen the effect of protest diffusion. Moreover, recent works have presented evidence of diffusion of specific types of protests, such as environmentalism (Reeder, Arce, and Siefkas 2022), racial justice (Beaman 2021) and domestic violence (Piatti-Crocker 2021).

This diffusion can be attributed to several potential mechanisms. First, scholars on "transnational social movements" point to international networks of actors interested in promoting goals on a global scale which connect and mobilize individuals across the country (Smith 2013; Keck and Sikkink 2014; Kozłowski 2021; Andrews and Biggs 2006). For example, Beissinger (2009) finds significant evidence that the networks of pro-democracy activists in the post-Soviet states was necessary to spread information allowing these groups to take advantage of autocratic weaknesses (see also Abdelrahman 2011). These networks allow for movements in other countries to learn how to organize themselves (Braithwaite, Braithwaite, and Kucik 2015; Tarrow 2011), the sharing of resources (Escribà-Folch, Meseguer, and Wright 2018; Tarrow 2011), and common actors participating in protests (Smith 2013; Keck and Sikkink 2014; Tarrow 2011).

Alternatively, several studies focus on the indirect effects of past protests on subsequent demonstrations. For instance, Bamert, Gilardi, and Wasserfallen (2015) find that protests that led to a regime change were more likely to be imitated elsewhere regardless of transnational actors. The success of a protest in one country sparks related protests in another. This builds off well established theory on social movements that the greater perceived likelihood of success, the more likely people are to join movements (Granovetter 1978). Protests abroad or in the past can send signals about what is possible, and if successful, what can be achieved through activism (Kuran 1991). Indeed, several studies find significant media effects wherein coverage of protests leads them to emerge elsewhere (Huang, Boranbay-Akan, and Huang

2019; Kozłowski 2021). While we are unable to test specific mechanisms using the data at hand, this extant work sheds light on the potential pathways through which protests should spread from one country to another across time and lead to the following testable hypotheses:

H1 **Spatial Diffusion**: As the number of protests increase abroad, the frequency of protests in a given country will increase.

H2 **Temporal Diffusion**: As the number of protests increases in the past, the frequency of protests at a given time will increase.

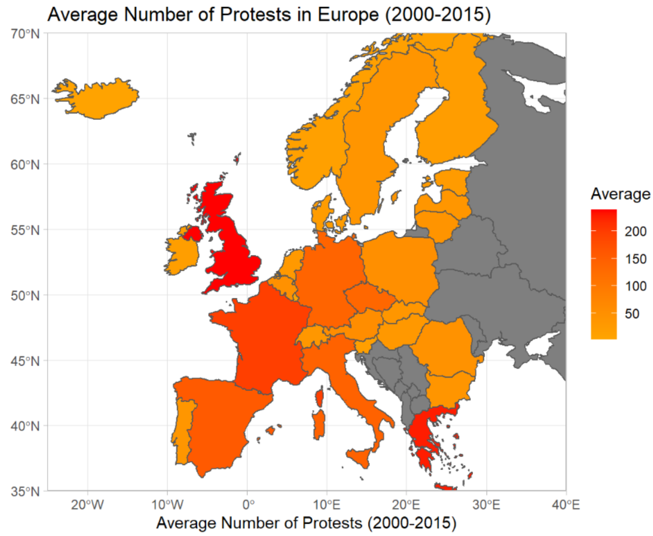
3. Research Design

3.1 Measuring the Dependent Variable: Protest

In this study, we use protest event data from the "*Political Conflict in Europe in the Shadow of the Great Recession (POLCON)*" dataset (see Kriesi et al. 2020). Through the machine coding of news stories covering protest events (PEA) the dataset provides information on 17,048 protests in 26 EU member states, Iceland, Norway, Switzerland, and the United Kingdom. We aggregate these protest events to country-level indicators of protest frequency, resulting in 465 observations of protest frequency at the country-year level, covering a period of 16 years (2000-2015).[3]

Figure 1 plots the geographic distribution of political protests throughout Europe via the average number of protests in a given year using data from 2000-2015.[4] As depicted in Figure 1, we can see that countries such as the United Kingdom, Spain, France, and Greece have high protest frequency. Meanwhile, East Europe and Northern Europe seem to have low levels of protest frequency, suggesting that there are important spatial dynamics at work that we aim to unpack.

3. It is worth noting that our dataset is unbalanced.
4. We use survey weights accounting for population.



Source: Authors' own calculation based on POLCON data

Figure 1. Geographic Distribution of Total Number of Protests, 2000-2015

3.2 Control Variables

To isolate the effect of protests abroad and in the past from systemic accounts, we include a number of control variables at the country level that may otherwise confound the hypothesized relationships of protest diffusion. To obtain these controls, we use the Comparative Politics Data Set (CPDS, Armingeon et al. 2017).

First, we account for levels of economic inequality at a given time as we expect inequality to serve as a useful proxy for feelings of relative deprivation. Some work suggests we should expect a positive relationship between inequality and protest frequency (Kurer et al. 2019; Grasso and Giugni 2016) while other studies find demobilizing effects of inequality (Solt 2015). Regardless, we expect economic inequality to shape protest frequency given its close relationship to economic grievances and relative deprivation. We rely on the Standardized World Income Inequality Database (SWIID) to provide cross-national data on the GINI coefficient Solt (2021).

Additionally, we incorporate other economic variables such as economic openness, GDP growth (the percentage change in real GDP per capita), unemployment rate, and education spending (as a percent of the GDP) to capture the macroeconomic environment. We expect economic openness to negatively relate to protest, since citizens will be less capable of assigning blame for economic outcomes (Hollyer, Rosendorff, and Vreeland 2015). Our expectations are ambiguous regarding GDP growth and unemployment rate (e.g., Kurer et al. 2019; Hollyer, Rosendorff, and Vreeland 2015).

Then, we control for political polarization and fractionalization. We expect more fractionalized time periods to be associated with more protests. In more fractional and polarized environments, compromise is needed more to govern and also punished by voters, which may lead to more protests (Nonnemacher 2022).

Finally, we consider political factors such as the percentage of women in parliament, voter turnout –representing the permeability of institutions to disadvantaged voices– and political alignment of the government. These factors have an impact on the need for protests, with higher representation of women in parliament and voter turnout potentially reducing the need for protests and a left-leaning government potentially increasing the frequency of protests.

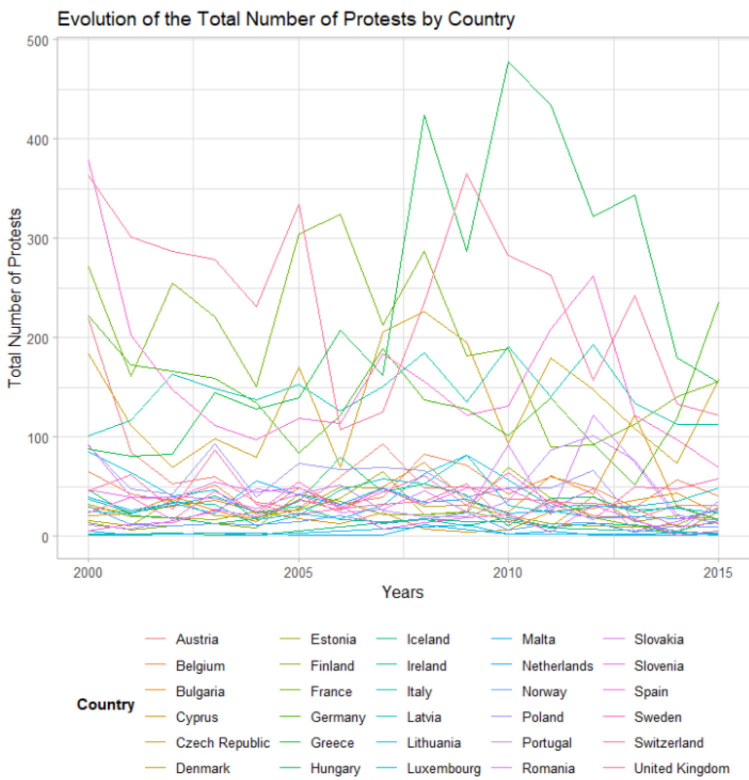
3.3 Modeling Spatial and Temporal Protest Across Countries

To specify the model, we must first conduct several diagnostics to test the presence of temporal and spatial dependence and whether we need to account for unique country factors.

3.3.1 Temporal

Figure 2 depicts the variation across time by country, and demonstrates temporal trends regarding the frequency of protest. For instance, we see a clear peak in protests in 2008, which is the highest number of protests in the period of analysis. This is not surprising since it correlates with the financial crisis that began in 2008 which would lead to the Eurocrisis. In particular, the highest value, corresponds to the 424 Greek protests in 2008 (green line).

To further unpack the dynamics across time, we run a Ljung-Box test to analyze the relationship of the residuals.[5] With no adjustments made, we reject the null hypothesis that our residuals are generated by a white noise process. This result demonstrates the presence of temporal dependence in the total number of protests.[6]



Source: Authors' own calculation based on POLCON data

Figure 2. Variation of Protest Frequency Across Time

Next, we conduct ACF and PACF tests (see Appendix 1) to examine temporal dependence, and find an AR(2) process. This suggests our model should incorporate two lagged dependent variables (LDV). To confirm whether the correlation of the residuals is resolved with the two LDVs, we re-run the Ljung-Box test, and conclude that with one-year LDV we still reject the null. However, we fail to reject the null with two lags, confirming that it takes two lags to overcome the white noise problem. These results provide some preliminary

5. The full results are reported in the appendix.
6. See also the residual plot reported in the appendix

support for **H2**. Protests in one year appear to be a function of the number of protests from at least two years prior.

3.3.2 Spatial Dependence

Now that we have identified a source of temporal dependence, we turn our attention to whether protests diffuse across borders. We start by using post-estimation diagnostic tests over models that only account for temporal dependence. We use the Lagrange Multiplier test as a diagnostic (Franzese and Hays 2008). We reject the null hypotheses for both the robust Lagrange Multiplier error test and the robust Lagrange Multiplier lag test, which suggest that to account for spatial dependence, we must account for bias from both measurable variables and unobservable processes of diffusion, i.e, do not restrict rho (ρ) nor lambda (λ) to be zero. These results represent evidence in favor of **H1**. Thus, to understand protest we need to account for spatial dependence and use a Spatial Autocorrelation (SAC) model. [7]

3.3.3 The model

Lastly, before estimating the models, we evaluate the need to account for a given countries' idiosyncrasies. Figures 1 and 2 show heterogeneous patterns of protest across countries. We run several tests to determine if we have intercept heterogeneity and how to address it. First, we run a *Lagrage multiplier test (Breusch-Pagan)* in which we reject the null hypothesis, which tells us that random effects perform better than a pooled OLS model. Then we run an *F-test* in which we also reject the null hypothesis, telling us fixed effects also perform better than a pooled OLS model. Thus, we should account for intercept heterogeneity across countries. To determine whether to use fixed effects or random effects, we run a *Hausman test*, and we reject the null hypothesis, which tells us that we should use fixed effects. In sum, we should also account for intercept heterogeneity by including fixed effects (FE) by countries.[8]

7. To assess for spatial dependencies (H1) we create a geographic (k-nearest neighbor) spatial weights matrix with three neighbors using an R function that is automated to create a spatial-lag weighting matrix with unbalanced country-year time-series cross section (TSCS) data Hays et al. 2022.

8. See Appendix 1 for full results and the explanation for every step.

In short, these diagnostic tests tell us that in order to receive an unbiased picture of protest diffusion, we need to implement a STADL model with FE by country. We expect the spatial parameters (H1) and the LDV (H2) to be significantly different from zero. Therefore, we estimate a linear regression model that takes the following form:

$$y = \rho W y + \gamma L y + \beta X + \alpha_i + \epsilon$$

where Y, is the total number of protests in country i at year t; L is a temporal lag operator L that produces a temporal lag of the outcome variable by incorporating $y_{i,t-1}$ and $y_{i,t-2}$ to account for temporal dependence; W represents the spatial weights matrix; ρ captures the spatial dependence across geographic units (using 3 neighbors);[9] X_{it} captures various institutional, and economic independent variables in our analysis; α_i is a country-specific intercept capturing possible unobserved country effects (intercept heterogeneity). Lastly, there is ϵ, which is:

$$\epsilon = \lambda W \epsilon + \mu$$

where λ represents the correlation among the errors and spatial correlation.

4. Results

Having implemented several tests to inform our model specification, Table 1 presents the results of our analysis. Columns 1 and 2 present the non-spatial nor temporal model (OLS) and a model addressing temporal dependence, but not spatial dependence respectively. These models help us to highlight the importance of accounting for both temporal and spatial dependence in the same model for our inferences. Next, columns 3 and 4 contain the Spatial Autoregressive (SAR) model and the Spatial Dependence Error Model (SDEM) respectively. These models have in common that spatial heterogeneity arises from a single

9. As a robustness check we also estimated the model looking at five neighbors, and also split the dataset by every two years and re-ran all estimations. These results are reported in Appendix 2, and are substantively the same.

source, constraining the other possible sources to zero. While the SAR model assumes clustering in the outcomes (spillovers/externalities), the SDEM implies spatial dependence comes from unmeasured covariates. Finally, columns 5 and 6 present the SAC model allowing both sources of dependency with and without fixed effects by country.

To begin, if we look at the OLS model we may infer that the number of protests is explained by several variables: voter turnout, women in parliament, economic openness, GDP growth, education spending, and income inequality. However, only a few of these effects survive once we account for spatio-temporal dependence. For example, economic inequality has the largest marginal effect according to column 1; however, the magnitude drops by roughly five times, and it is no longer statistically significant in column 2. Additionally, there are also important changes in GDP growth, which according to column 1 is a key predictor of protest frequency. While its effect survives in the best model specification (SAC with FE), the effect we observe in column 6 is notably smaller than in the OLS model. Interestingly, when we only account for temporal diffusion, the effect of GDP growth disappears, but returns when we then factor in spatial dependence, further demonstrating the importance of accounting for both sources of bias in the same model.

Importantly for H2, in column 2, both lag variables are statistically significant, indicating that without accounting for spatial dependence, protest frequency from two years prior predicts the frequency of protests today, in line with H2. However, when we account for spatial dependence, we see that the two-year lag loses significance and the coefficient for the one-year lag nearly halves, which demonstrates how models that do not account for spatial dependence when attempting to study protest diffusion will arrive at overestimations of the true nature of temporal diffusion.

More specifically, Table 1 presents empirical evidence consistent with **H1**. We confirm spatial dependence dynamics since both the estimates for ρ (clustering in the outcomes) and λ (cluster in unobservables) are statistically significant. Specifically, the spatial autoregressive parameter ρ, which measures the strength of the spatial interdependency, denotes a positive spatial dependence. Substantively, this means that as the frequency of protest increases in neighboring countries, protests will increase at home. Moreover, we reject the null hypothesis for λ, meaning that there is also spatial autocorrelation in the errors.

Table 1. Results from multivariate regression (DV Total Number of Protests)

	OLS	OLS+lag	SAR+FE	SDEM+FE	SAC	SAC + FE
LDV 1		0.583^{***}	0.246^{***}	0.274^{***}	0.613^{***}	0.298^{***}
		(0.052)	(0.056)	(0.056)	(0.051)	(0.055)
LDV 2		0.219^{***}	-0.021	-0.045	0.177^{***}	-0.057
		(0.048)	(0.049)	(0.050)	(0.046)	(0.049)
Unemployment	-1.017	-0.533	0.242	0.417	-0.258	0.636
	(0.745)	(0.491)	(0.720)	(0.719)	(0.449)	(0.711)
Left Government	0.065	0.084	-0.031	-0.026	0.042	-0.040
	(0.084)	(0.055)	(0.055)	(0.055)	(0.051)	(0.054)
Vote Turnout	0.819^{**}	0.274	-0.081	-0.123	0.213	-0.208
	(0.260)	(0.174)	(0.428)	(0.427)	(0.155)	(0.422)
Women Parliament	-0.912^{**}	-0.408	-1.763^{***}	-1.710^{***}	-0.271	-1.792^{***}
	(0.336)	(0.221)	(0.475)	(0.472)	(0.203)	(0.466)
Economic Openess	-0.592^{***}	-0.109^{*}	0.134	0.120	-0.087^{*}	0.183
	(0.062)	(0.044)	(0.129)	(0.128)	(0.041)	(0.130)
GDP growth	-2.164^{*}	-0.444	-0.960	-0.914	-0.579	-1.077^{*}
	(0.864)	(0.538)	(0.528)	(0.524)	(0.509)	(0.521)
Fractionalization	-9.879	32.077	-45.611	-58.168	23.756	-62.595
	(43.103)	(27.652)	(53.478)	(52.905)	(24.741)	(51.535)
Education Spending	-19.679^{***}	-4.075	-4.626	-3.520	-4.104^{*}	-4.827
	(3.180)	(2.151)	(4.135)	(4.083)	(1.964)	(4.086)
Gini	381.839^{***}	83.547	-0.717	-14.209	34.847	-42.769
	(74.626)	(49.089)	(131.175)	(131.859)	(44.317)	(131.176)
Lambda				**-0.120**	$\mathbf{-0.284}^{**}$	$\mathbf{-0.272}^{**}$
				(0.075)	(0.093)	(0.101)
Rho			**0.036**		$\mathbf{0.133}^{**}$	$\mathbf{0.122}^{*}$
			(0.047)		(0.044)	(0.057)
N	411	360	360	360	360	360
R^2	0.342	0.744	0.806	0.807	0.757	0.812
Log Likelihood	-2244.045	-1776.761	-1727.203	-1726.590	-1771.534	-1724.462
AIC	4510.091	3579.522	3540.406	3539.181	3573.069	3536.925

*** p <0.001; ** p <0.01; * p <0.05.

To put these results in context, we can desegregate the effects of GDP grwoth, which is an illustrative example, into direct and indirect impacts (see LeSage and Fischer (2010) and Whitten, Williams, and Wimpy 2021).[10] The indirect impact which results from the effects of neighbors represents 12% of the total effect. Overall, these results tell us about the importance of accounting for spatial dependence, even though we have control variables, lagged dependent variables, and fixed effects. Substantively, this demonstrates the spatial contagiousness of protests.

The empirical analysis also provides evidence consistent with the theoretical expectations behind **H2** about temporal dependence. High level of protests at time $t-1$ predicts protests in time t, given that we reject the null hypothesis of no temporal dependence regarding the one-year lagged dependent variable. Regarding time-dependence we can see that if the protest frequency is 100 at time $t-1$, then there will be an increase of about 30 protests at time t. Interestingly, we do not find a significant effect of protests two years prior, which suggests that by controlling for confounding variables and spatial dynamics, we have accounted for much of what originally appeared as temporal dependence. The robustness of a significant one year lag with these controls and the spatial dependence gives confidence that this is not a spurious finding.

Finally, Table 1 shows that the SAC model with fixed effects is the best fit as it has the lowest value of *AIC*. Notably, in this model both ρ, and λ remain statistically significant as does our one year lag dependent variable.

Turning now to our covariates, Table 1 provides interesting findings. First, we find a the more women in legislative roles, the less protests. We suspect this could be a sign that more representative institutions decrease the need for unconventional forms of participation. Next, we find no significant effect of the ideology of government. Unsurprisingly, we find that a growing economy decreases the average number of protests. The better the economy is doing, the less grievances individuals may have. We also find evidence that welfare spending

10. See full desegregation of direct and indirect effects in Spatial Appendix.

may decrease protests, but this is not robust to the inclusion of FE by country. Interestingly, we also fail to find robust effects for the GINI coefficient, unemployment, and economic openness.

5. Conclusion

In this paper, we have analyzed the temporal and spatial dynamics of political protests in Europe using the novel STADL model. First, we find significant spatial diffusion of protest events across neighboring countries, which is statistically significant even after controlling for alternative explanations of protest. Then, we find significant temporal dependence from at least one year. The presence of ***both*** temporal and spatial dependence contribute to our understandings of political protests and their contagious nature.

We have applied the STADL model, recommended by Cook, Hays, and Franzese (2022), to our cross-sectional time-series data analysis to avoid potential spurious inferences. Our results provide important insight into the dynamics of protest diffusion and challenge prior claims that protests do not diffuse, supporting the literature that protests are shaped by protests in the past and nearby. The STADL model, allows for more unbiased estimates of the effect of covariates, accounting for both temporal and spatial lags, which previous work may have neglected, leading to spurious conclusions. Our findings, including the statistically insignificant effect of inequality on protest frequency, contribute to resolving unsettled theoretical questions in the literature.

These findings highlight the contagious nature of protests across time and space. Future research should examine the underlying mechanisms of diffusion, including geographical proximity, communication channels, organizational networks, and media consumption. Additionally, it would be valuable to study protest diffusion in regions outside Europe, where the permeability of borders and access to common media may impact its diffusion.

6. Competing interests

The author(s) declare none.

References

Abdelrahman, Maha. 2011. The Transnational and the Local: Egyptian Activists and Transnational Protest Networks. *British Journal of Middle Eastern Studies* 38 (3): 407–424.

Aidt, Toke, and Gabriel Leon-Ablan. 2022. The Interaction of Structural Factors and Diffusion in Social Unrest: Evidence from the Swing Riots. *British Journal of Political Science* 52 (2): 869–885.

Andrews, Kenneth T., and Michael Biggs. 2006. The Dynamics of Protest Diffusion: Movement Organizations, Social Networks, and News Media in the 1960 Sit-Ins. *American Sociological Review* 71 (5): 752–777.

Armingeon, Klaus, Virginia Wenger, Fiona Wiedemeier, Christian Isler, Laura Knöpfel, David Weisstanner, and Sarah Engler. 2017. Codebook: Comparative Political Data Set 1960–2015. *Institute of Political Science, University of Bern: Bern, Switzerland.*

Bamert, Justus, Fabrizio Gilardi, and Fabio Wasserfallen. 2015. Learning and the diffusion of regime contention in the Arab Spring. *Research & Politics* 2 (3).

Beaman, Jean. 2021. Towards a Reading of Black Lives Matter in Europe. *JCMS: Journal of Common Market Studies* 59:103–114.

Beissinger, Mark R. 2009. Debating the Color Revolutions: An Interrelated Wave. *Journal of Democracy* 20 (1): 74–77.

Box-Steffensmeier, Janet M., John R. Freeman, Matthew P. Hitt, and Jon C. W. Pevehouse. 2014. *Time Series Analysis for the Social Sciences.* Cambridge University Press, December.

Braithwaite, Alex, Jessica Maves Braithwaite, and Jeffrey Kucik. 2015. The conditioning effect of protest history on the emulation of nonviolent conflict. *Journal of Peace Research* 52 (6): 697–711.

Brancati, Dawn, and Adrián Lucardi. 2019a. What We (Do Not) Know about the Diffusion of Democracy Protests. *Journal of Conflict Resolution* 63 (10): 2438–2449.

———. 2019b. Why Democracy Protests Do Not Diffuse. *Journal of Conflict Resolution* 63 (10): 2354–2389.

Bunce, Valerie J., and Sharon L. Wolchik. 2006. International diffusion and postcommunist electoral revolutions. *Communist and Post-Communist Studies* 39 (3): 283–304.

Cook, Scott J., Jude C. Hays, and Robert J. Franzese. 2022. STADL Up! The Spatiotemporal Autoregressive Distributed Lag Model for TSCS Data Analysis. *American Political Science Review,* 1–21.

Escribà-Folch, Abel, Covadonga Meseguer, and Joseph Wright. 2018. Remittances and Protest in Dictatorships. *American Journal of Political Science* 62 (4): 889–904.

Franzese, Robert J., and Jude C. Hays. 2007. Spatial Econometric Models of Cross-Sectional Interdependence in Political Science Panel and Time-Series-Cross-Section Data [in en]. *Political Analysis* 15 (2): 140–164.

———. 2008. *Empirical Models of Spatial Inter-Dependence* [in en].

Gleditsch, Kristian S., and Mauricio Rivera. 2017. The Diffusion of Nonviolent Campaigns. *Journal of Conflict Resolution* 61 (5): 1120–1145.

Granovetter, Mark. 1978. Threshold Models of Collective Behavior. *American Journal of Sociology* 83 (6): 1420–1443.

Grasso, Maria T., and Marco Giugni. 2016. Protest participation and economic crisis: The conditioning role of political opportunities [in en]. *European Journal of Political Research* 55 (4): 663–680. https://doi.org/10.1111/1475-6765.12153.

Hale, Henry E. 2019. How Should We Now Conceptualize Protest, Diffusion, and Regime Change? *Journal of Conflict Resolution* 63 (10): 2402–2415.

Hays, Jude C., Valentina González-Rostani, Scott Cook, Robert Franzese, and Wooseok Kim. 2022. *The tscsdep package. Tools for analyzing country-year time-series-cross-sectional data with spatial and temporal dependence.* https://github.com/judechays/STADL.

Hollyer, James R., B. Peter Rosendorff, and James Raymond Vreeland. 2015. Transparency, Protest, and Autocratic Instability. *American Political Science Review* 109 (4): 764–784.

Huang, Haifeng, Serra Boranbay-Akan, and Ling Huang. 2019. Media, Protest Diffusion, and Authoritarian Resilience. *Political Science Research and Methods* 7 (1): 23–42.

Keck, Margaret E., and Kathryn Sikkink. 2014. *Activists beyond Borders: Advocacy Networks in International Politics.* Cornell University Press.

Kern, Holger Lutz. 2011. Foreign Media and Protest Diffusion in Authoritarian Regimes: The Case of the 1989 East German Revolution. *Comparative Political Studies* 44 (9): 1179–1205.

Kozłowski, Tomasz. 2021. From Strikes to Solidarity: The Diffusion of Protests in Poland in the Summer of 1980. *East European Politics and Societies* 35 (4): 1161–1178.

Kriesi, Hanspeter, E. Grande, S. Hutter, A. Altiparmakis, E. Borbáth, S. Bornschier, B. Bremer, M. Dolezal, T. Frey, and T. Gessler. 2020. *PolDem-National Election Campaign Dataset, Version 1.*

Kuran, Timur. 1991. Now out of never: The element of surprise in the East European revolution of 1989. *World politics* 44 (1): 7–48.

Kurer, Thomas, Silja Häusermann, Bruno Wüest, and Matthias Enggist. 2019. Economic grievances and political protest. *European Journal of Political Research* 58 (3): 866–892.

LeSage, James P., and Manfred M. Fischer. 2010. Spatial Econometric Methods for Modeling Origin-Destination Flows. In *Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications,* edited by Manfred M. Fischer and Arthur Getis, 409–433. Berlin, Heidelberg: Springer.

Lichbach, Mark. 1985. Protest: Random or Contagious?: The Postwar United Kingdom. *Armed Forces & Society* 11 (4): 581–608.

Nonnemacher, Jeffrey. 2022. Representational deprivation: niche parties, niche voters and political protest. *West European Politics,* 1–25.

Piatti-Crocker, Adriana. 2021. Diffusion of #NiUnaMenos in Latin America: Social Protests Amid a Pandemic. *Journal of International Women's Studies* 22, no. 12 (November): 7–24.

Porta, Donatella della, ed. 2017. *Global Diffusion of Protest. Riding the Protest Wave in the Neoliberal Crisis.* Amsterdam University Press.

Reeder, Bryce W., Moises Arce, and Adrian Siefkas. 2022. Environmental justice organizations and the diffusion of conflicts over mining in Latin America. *World Development* 154.

Smith, Jackie. 2013. Transnational Social Movements. In *The Wiley-Blackwell Encyclopedia of Social and Political Movements.* John Wiley & Sons, Ltd.

Solt, Frederick. 2015. Economic Inequality and Nonviolent Protest*. *Social Science Quarterly* 96 (5): 1314–1327.

———. 2021. *The Standardized World Income Inequality Database (SWIID).*

Strauch, Rebecca, and Nils B. Weidmann. 2022. Protest and digital adaptation. *Research & Politics* 9 (2).

Tarrow, Sidney G. 2011. *Power in Movement: Social Movements and Contentious Politics.* Cambridge University Press.

Way, Lucan. 2008. The Real Causes of the Color Revolutions. *Journal of Democracy* 19 (3): 55–69.

Whitten, Guy D., Laron K. Williams, and Cameron Wimpy. 2021. Interpretation: the final *spatial* frontier. *Political Science Research and Methods* 9 (1): 140–156.

Appendix 1. Appendix

For a full breakdown of our analysis, we have two Online Appendices:

1. Appendix containing the time dependence and intercept heterogeneity analysis.
2. Appendix containing the spatial dependence analysis for three and five neighbors.