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Are Protests Contagious? The Dynamics of Temporal and Spatial Diffusion of Political Protests

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Abstract

Do political protests diffuse across time and space? While scholars of social movements and political behavior have long debated this question, existing studies often fail to simultaneously account for both spatial and temporal dependencies in protest dynamics. Using protest event analysis and a novel spatiotemporal autoregressive distributed lag (STADL) model, we examine the diffusion of protests across 26 European countries from 2000 to 2015. Our findings provide robust evidence that protests exhibit both temporal and spatial contagion: protest activity in one year significantly increases protest frequency in the following year, and protests in one country contribute to the onset of protests in neighboring states. These results underscore the importance of modeling both dimensions of diffusion to avoid biased inferences and contribute to the broader understanding of protest mobilization. Our study highlights the interconnected nature of political activism and has important implications for research on social movements and political instability.

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

1. Introduction

In August 2018, Greta Thunberg staged a small-scale protest outside the Swedish parliament, denouncing the failure of Swedish elites to adequately address climate change. What began as an isolated demonstration quickly gained momentum, inspiring students and activists across Sweden. By 2019, the movement—known as *Fridays for Future*—had expanded beyond Sweden's borders, spreading first to neighboring countries, including Norway, Finland, and Denmark, before gaining traction across the Baltic Sea in Germany and Poland. This pattern of diffusion is evident in early strike participation: between December 2018 and March 2019, there were 261 demonstrations in Sweden, followed by 41 in Finland, 18 in Norway, 30 in Poland, and 215 in Germany.[1] A similar pattern of protest diffusion emerged in 2020 after the death of George Floyd in the United States. What began as a domestic movement against racial injustice quickly spread beyond US borders, first igniting protests in neighboring Canada and Mexico before inspiring demonstrations worldwide.[2] These examples illustrate how political protests may propagate across both space and time—but do they genuinely diffuse from one country to another, or do similar structural conditions independently produce mobilization?

Scholars remain divided on this question. Some argue that revolutionary waves demonstrate clear protest contagion (Porta 2017; Strauch and Weidmann 2022), while others contend that protests emerge independently due to shared structural conditions (Way 2008; Brancati and Lucardi 2019b). Despite this debate, research has largely examined spatial and temporal diffusion separately, leaving their simultaneous occurrence understudied. To address this gap, we implement an approach that models both dimensions jointly using cross-sectional time-series data (e.g., Box-Steffensmeier et al. 2014; Franzese and Hays 2007, 2008; Strauch and Weidmann 2022).

Several mechanisms could drive spatiotemporal protest diffusion. Transnational activist networks spread mobilization strategies across borders (Keck and Sikkink 2014; Smith 2013),

1. See fridaysforfuture.org.
2. See List of George Floyd protests outside the United States and Politico.

while organizational legacies sustain activism over time by lowering coordination costs and preserving movement infrastructure (Mazumder 2018). Repeated protests may also normalize dissent and inspire further action through increased feelings political efficacy. Together, these dynamics suggest that protests not only spread across countries, but also persist over time.

To properly account for these dynamics, we employ a spatiotemporal autoregressive distributed lag (STADL) model (Cook, Hays, and Franzese 2022), which allows us to analyze both spatial and temporal dependence in a unified framework. Using protest event analysis (PEA) data aggregated at the country level across 26 European nations, we find strong evidence that protests diffuse both geographically and over time—with mobilization in one country influenced by both prior domestic protests and protest activity in neighboring states. Beyond the substantive implications for protest diffusion, our study underscores key methodological concerns: failing to account for spatiotemporal dependence can bias statistical estimates, misattributing the effects of political, economic, or structural factors that shape protest dynamics.

This paper proceeds as follows. First, we review the literature on protest diffusion and outline our theoretical expectations. We then present our methodological approach and STADL model. Finally, we discuss our findings and their implications for the study of protests.

2. Political Protest Across Space and Time

The spread of protests over time and across countries has been extensively studied in the literature on protests and social movements, yet the contagious nature of protests remains debated (Brancati and Lucardi 2019a; Porta 2017). Much of this research focuses on pro-democracy movements, such as the 1989 protests in Eastern Europe, the Color Revolutions of the early 2000s, or the Arab Spring. However, scholars are divided on whether protests genuinely diffuse across borders and over time, or whether observed patterns are simply the result of shared domestic conditions.

On one hand, several studies argue that protest diffusion has been overstated, particularly for democratic revolutions, and that mobilization is best understood through domestic structural factors rather than cross-national influences (Brancati and Lucardi 2019b; Bunce and Wolchik 2006; Hale 2019; Kern 2011; Way 2008). For instance, Way (2008) challenges the idea of an "interrelated wave" during the Color Revolutions, instead attributing protests to similar internal conditions in each country. Similarly, Brancati and Lucardi (2019b) contends that democratic protests do not spread across borders because they focus on domestic-level reforms that are largely unaffected by transnational actors. From this perspective, protests that appear to be spreading may simply be emerging independently due to comparable domestic grievances.

On the other hand, extensive research finds strong empirical support for protest diffusion (Porta 2017; Gleditsch and Rivera 2017; Lichbach 1985; Keck and Sikkink 2014; Strauch and Weidmann 2022). Aidt and Leon-Ablan (2022) argue that structural factors and diffusion work in tandem, where conducive domestic conditions amplify the effects of transnational protest waves. Recent work also documents diffusion within specific issue-based movements, such as environmental protests through Fridays for Future (Reeder, Arce, and Siefkas 2022), racial justice movements such as Black Lives Matter (Beaman 2021), and mobilization against domestic violence (Piatti-Crocker 2021). These studies suggest that protest diffusion is not just a byproduct of similar structural conditions but a real phenomenon with identifiable mechanisms.

2.1 How Protests Spread: Mechanisms of Diffusion Over Time and Space

Understanding the persistence of protests across both space and time requires a theoretical framework that accounts for transnational diffusion and temporal continuity. One prominent explanation for spatial diffusion comes from research on transnational social movements, which emphasize how international networks of activists, organizations, and media spread protest strategies and narratives across borders (Smith 2013; Keck and Sikkink 2014). Citizens and transnational activists take cues from events unfolding abroad (see Nonnemacher, Forthcoming). For example, Beissinger (2009) finds that networks of pro-democracy activists in post-Soviet states helped disseminate information on regime weaknesses, facilitating mobilization across multiple countries (see also Abdelrahman 2011). These networks enable movements to share tactical knowledge (Braithwaite, Braithwaite, and Kucik 2015; Tarrow 2011), pool material and human resources (Escribà-Folch, Meseguer, and Wright 2018; Tarrow 2011), and mobilize common actors across different national contexts (Smith 2013; Keck and Sikkink 2014).

Beyond direct actor-based diffusion, indirect learning mechanisms also facilitate protest spillovers across borders. Media coverage of protests in neighboring countries-similar to one's own country– can signal the possibility of successful mobilization, leading activists in other countries to emulate these movements (Huang, Boranbay-Akan, and Huang 2019; Kozłowski 2021). Additionally, protests that successfully lead to political change can increase expectations of success elsewhere. Bamert, Gilardi, and Wasserfallen (2015), for example, finds that movements resulting in regime change tend to be imitated abroad, consistent with theories of threshold-based participation where individuals are more likely to join protests when they believe a certain threshold of others are participating and success is achievable (Granovetter 1978; Kuran 1991).

These mechanisms largely explain the diffusion of protests across borders. While they also apply to temporal diffusion, additional processes contribute to the continuity of protests over time. Prior mobilization creates lasting organizational legacies, enabling future protests by reducing coordination costs and maintaining activist networks. Research on the US civil rights movement illustrates how early mobilization shaped political attitudes and activism for years afterward, sustaining engagement beyond the initial protests (Mazumder 2018). Similarly, movements such as "MeToo" demonstrate how the acknowledgment of grievances and the creation of activist networks facilitate long-term protest sustainability (Suk et al. 2021).

Protests over time also have important consequences for those who participate in them, creating legacies of participation that are likely to carry over into future demonstrations. As Finkel (1985) demonstrates, political participation can have reciprocal consequences such that participation can foster heightened feelings of political efficacy, which contribute to subsequent participation (Oser et al. 2022). This can, in turn, expand activist networks and deepen social ties among participants that sustains political engagement (Bursztyn et al. 2021). Additionally, as protests become more visible and widespread, they may signal an increased tolerance for dissent, further encouraging participation and sustaining mobilization cycles (Cantoni et al. 2024).

In summary, there are potentially multiple mechanisms at work that support the contagious nature of political protests. Across borders, the development of transnational activists and learning from abroad can contribute to similar demonstrations appearing in other countries. Temporally, the establishment of organizational legacies around protest and heightened political efficacy can foster repeated protest activity.

2.2 Empirical Implications and Testable Hypotheses

Identifying the specific mechanisms driving protest diffusion is beyond the scope of this study, as the data at hand do not allow for a direct test of these pathways. Instead, our focus remains on determining whether spatiotemporal dependence exists. Establishing this dependence is a crucial step for future research to explore the precise causal mechanisms through which protests spread across countries and persist over time. To test this, we propose the following hypotheses:

Hypothesis 1 (Temporal Diffusion) *As the number of protests increases in the past, the frequency of protests at a given time will increase.*

Hypothesis 2 (Spatial Diffusion) *As the number of protests increases abroad, the frequency of protests in a given country will increase.*

Hypothesis 3 (Spatiotemporal Diffusion) *As the number of protests increases abroad and in the past, the frequency of protests at a given time in a given country will increase.*

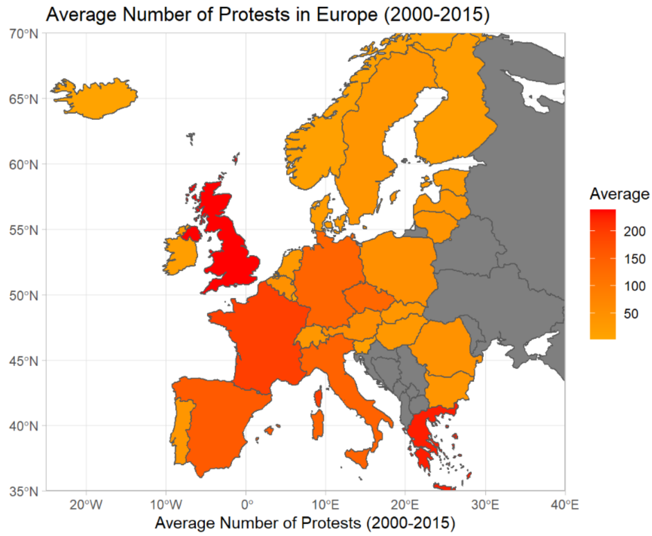
3. Research Design

3.1 Measuring the Dependent Variable: Protest

In this study, we use protest event data from the PolDem-Protest Dataset (Kriesi et al. 2020), where the unit of analysis is the protest event. This dataset, constructed through a hybrid approach combining machine learning and human coding of news reports, documents 17,048 protest events across 26 EU member states, Iceland, Norway, Switzerland, and the United Kingdom. Europe provides an ideal setting to test our hypotheses for several reasons. First, its ongoing integration fosters protest diffusion through transnational media, social movements, and increasingly, politics (Wolkenstein, Senninger, and Bischof 2020). If diffusion dynamics are undetectable in this highly interconnected region, they are even less likely to emerge in less integrated parts of the world. Second, Europe's strong press freedom and extensive data availability ensure a more comprehensive and reliable record of protest events. Unlike in more restrictive or underdeveloped information environments, this dataset provides a robust and reliable record of protests.

We aggregate protest events into country-year indicators of protest frequency, resulting in 465 observations covering 16 years (2000–2015).[3] Figure 1 presents the geographic distribution of protests across Europe, based on the average annual protest frequency during this period.[4] The data reveal high protest activity in the United Kingdom, Spain, France, and Greece, whereas Eastern and Northern Europe exhibit lower levels of protest. These patterns suggest underlying spatial dynamics that warrant further analysis.

3. The dataset is unbalanced.
4. Survey weights account for population differences.



Source: Authors' own calculation based on PolDem data.

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

3.2 Measuring Structural Factors Triggering Protest

Given our focus on the effects of past and foreign protests from a systemic perspective, we account for potential confounders that may drive protest activity. Prior research suggests that what appears to be protest contagion may instead reflect shared structural conditions that independently foster mobilization (Way 2008; Brancati and Lucardi 2019b). To address this, we incorporate key country-level factors that may explain protest occurrence and mitigate omitted variable bias in assessing protest diffusion. These variables are operationalized using the Comparative Politics Data Set (CPDS, Armingeon et al. 2017).

First, we consider economic inequality, which serves as a proxy for relative deprivation. While some studies suggest a positive relationship between inequality and protest frequency (Kurer et al. 2019; Grasso and Giugni 2016), others find demobilizing effects (Solt 2015; Gonzalez-Rostani 2024). Given its strong connection to economic grievances, we expect inequality to shape protest dynamics. We measure this factor using the Standardized World Income Inequality Database (SWIID), which provides cross-national GINI coefficient data Solt (2021).

Additionally, we incorporate macro-economic indicators, including economic openness, GDP growth (percentage change in real GDP per capita), unemployment rate, and education spending (as a share of GDP). Economic openness is expected to have a negative relationship with protest activity, as citizens may find it more difficult to attribute economic outcomes to domestic policies (Hollyer, Rosendorff, and Vreeland 2015). Similarly, GDP growth, as an indicator of economic prosperity, is anticipated to reduce protest frequency. However, the relationship between unemployment and protest remains ambiguous, as prior research presents mixed findings (e.g., Kurer et al. 2019; Hollyer, Rosendorff, and Vreeland 2015).

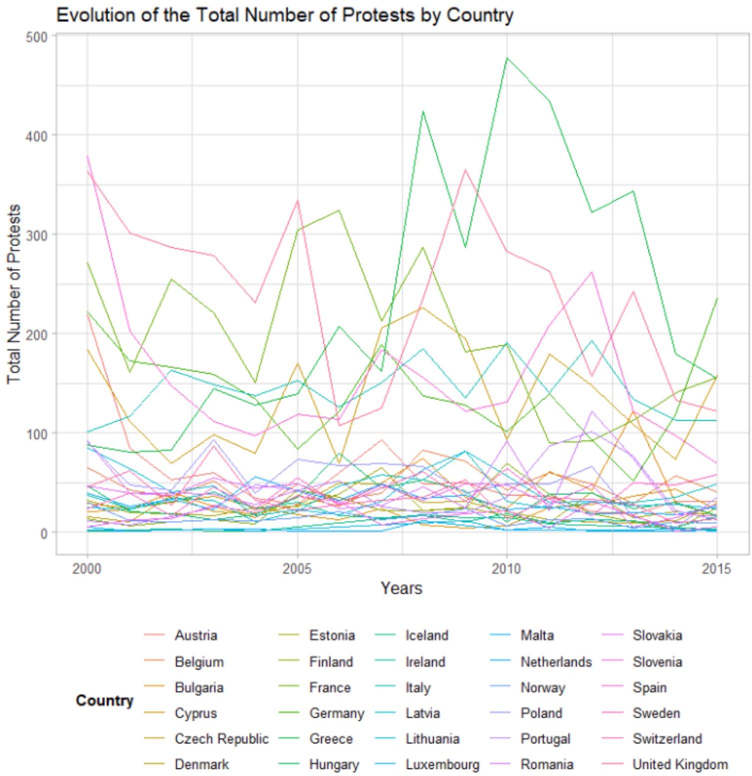
Next, we account for political polarization and fractionalization, anticipating that greater fractionalization correlates with increased protest frequency. In highly polarized contexts, governing requires greater compromise, which may both increase dissatisfaction and provoke voter backlash, leading to heightened protest activity (Nonnemacher 2022).

Finally, we incorporate political variables such as the percentage of women in parliament, voter turnout, and government ideology. Higher female representation and greater voter turnout—both indicators of institutional accessibility to marginalized groups—are expected to reduce protest demand. Conversely, left-leaning governments may experience higher protest frequency, potentially due to increased mobilization among politically engaged constituencies.

3.3 Modeling Spatial and Temporal Protest Across Countries

Building on recent advances in spatiotemporal econometrics (Cook, Hays, and Franzese 2022), we first assess whether temporal and spatial autoregressive models are necessary. Figure 2 illustrates protest frequency across time and countries, with a peak in 2008 coinciding with the global financial crisis. That year, Greece recorded the highest number of protests (424).

We test for temporal dependence using Ljung-Box tests and autocorrelation analyses, which identify an AR(2) process, indicating that protest frequency is influenced by events from the past two years. This supports Hypothesis 1 and justifies including two lagged dependent variables (LDVs) in our model.[5]



Source: Authors' own calculation based on PolDem data

Figure 2. Variation of Protest Frequency Across Time

Next, we assess whether protests diffuse across borders. Post-estimation diagnostic tests, including the Lagrange Multiplier test, as suggested by Franzese and Hays (2008), confirm the presence of spatial dependence, providing preliminary support for Hypothesis 2. The results indicate that spatial dependence extends beyond the spatial lag (ρ) and must also account for unobservable processes (spatial error, λ). Consequently, our model should be a Spatial Autocorrelation (SAC).[6]

5. Full test results are in Appendix 1, with a summary provided in Appendix 3.1.

6. To create the k-nearest neighbor spatial weights matrix with three neighbors, we use an R package designed for spatial-lag weighting matrices in unbalanced country-year time-series cross-sectional (TSCS) data (Hays et al. 2022). Full details on spatial dependence tests and alternative specifications are provided in Appendix 2 and Appendix 3.2.

Finally, we assess whether country-specific effects should be accounted for, with diagnostic tests supporting the use of a fixed-effects (FE) specification.[7] Based on these diagnostics, we estimate a spatiotemporal autoregressive distributed lag (STADL) model with country FE to obtain an unbiased estimate of protest diffusion. Accounting for both temporal and spatial dependence allows us to test Hypothesis 3, as follows.

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

where Y represents the total number of protests in country i at year t; L is a temporal lag operator that accounts for time dependence by incorporating $y_{i,t-1}$ and $y_{i,t-2}$; W denotes the spatial weights matrix; and ρ captures spatial interdependence across geographic units, using three nearest neighbors.[8] X_{it} includes institutional and economic covariates; α_i is a country-specific intercept capturing unobserved heterogeneity; and ϵ is the error term, defined as:

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

where λ captures error clustering, i.e., spatial effects in the unobservables. We expect both the spatial parameters and the lagged dependent variables (LDVs) to be statistically significant, indicating the presence of spatial and temporal dependence.

4. Results

Table 1 presents the results of our analysis, comparing various model specifications to assess the role of spatiotemporal dependence in protest frequency. Column 1 reports results from a standard OLS model that does not account for spatial or temporal dependencies, and Column 2 introduces temporal dependence. These initial models suggest that voter turnout, women's

7. Our diagnostic tests—the Lagrange Multiplier test (Breusch-Pagan), F-test, and Hausman test—are briefly explained in Appendix 3.3 and detailed further, along with robustness checks, in Appendix 1.

8. As a robustness check, we also estimated the model using five neighbors and conducted additional analyses by splitting the dataset into two-year intervals. The results, reported in Appendix 2, remain substantively unchanged.

parliamentary representation, economic openness, GDP growth, education spending, and income inequality are associated with protest frequency. However, these estimates are likely biased due to unaccounted-for spatial and temporal correlations. Once both dependencies are incorporated (Columns 3–6), many of these associations weaken or disappear, underscoring the importance of properly specifying the model to avoid misleading inferences.

Columns 3 and 4 present the spatial autoregressive model (SAR) and the spatial dependency error model (SDEM), which account for spatial clustering in outcomes (ρ) and unobserved factors (λ), respectively. Columns 5 and 6 estimate the SAC model, which jointly models spatial dependence in both outcomes and unobservables, with Column 6 incorporating country-level fixed effects. Comparing the OLS model (Column 1) with the SAC model (Column 6)—which provides the best fit based on AIC—reveals substantial attenuation in key coefficients. For example, economic inequality initially appears as a major determinant of protest frequency, but its effect diminishes nearly five times and loses statistical significance once spatial and temporal dependencies are considered. GDP growth remains significant but exhibits a reduced magnitude, and the proportion of women in parliament continues to have a robust negative association with protest frequency.

Turning to our main focus—spatiotemporal dependence—the inclusion of temporal lags confirms that protest frequency exhibits persistence over time, as indicated by the preliminary diagnostics. In the model without spatial dependence (Column 2) and the model incorporating spatial dependence but excluding fixed effects (Column 5), both the one- and two-year lags (L) are statistically significant, supporting Hypothesis 1. However, once fixed effects are incorporated, the two-year lag loses significance, suggesting that the effect does not persist indefinitely. In terms of magnitude, the one-year lagged protest variable indicates that a protest frequency of 100 in year $t-1$ is associated with approximately 30 additional protests in year t, reinforcing the short-term temporal diffusion of protests.

Regarding spatial dependence, models incorporating both interdependence (ρ) and clustering in the unobservables (λ) (Columns 5–6) confirm the presence of spatial autocorrelation. The positive ρ coefficient suggests that protest activity in one country increases when protests occur in neighboring countries, supporting Hypothesis 2. This suggests that observing protests in nearby countries can provide domestic actors with critical information about the potential benefits and risks of mobilization, influencing their own likelihood of protest. Thus, protests are shaped not only by local structural factors but also by external dynamics from surrounding areas. To illustrate the magnitude of spatial dependence, an increase of approximately 8 additional protest events in a region is associated with one additional protest event in a neighboring region, as captured by the ρ coefficient (0.122). This underscores the extent to which protest activity spreads across geographic boundaries, reinforcing the role of spatial interdependence in shaping patterns of mobilization.

Meanwhile, the significant λ coefficient suggests that unobserved factors influencing protests are spatially correlated in ways that may suppress protest activity in adjacent regions. These results highlight the dual mechanisms of spatial diffusion: direct protest contagion and the influence of regionally correlated unobserved conditions, such as political repression, regulatory constraints, or cultural legacies, in shaping protest patterns. Simply put, what happens in France can influence protests in Germany and other neighboring countries, which in turn may spark mobilization in their respective neighbors, creating a cascading effect across the region.

Overall, the STADL models are overwhelmingly preferred based on the AIC model-selection criteria, outperforming both the OLS model and the specification that accounts only for temporal dependence. Among the spatiotemporal models, the SAC model with fixed effects (Column 6) provides the best fit. In this specification, both ρ and λ remain statistically significant, along with the one-year lagged dependent variable (L), reinforcing the necessity of accounting for both spatial and temporal dependencies. These findings support Hypothesis 3 and highlight the risks of omitting such dependencies. The substantial changes in magnitude and statistical significance of key variables between the OLS model and the fully specified SAC model illustrate how failing to incorporate spatiotemporal dynamics can introduce bias, ultimately leading to misleading conclusions about the determinants of protest frequency.

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**	**-0.284****	**-0.272****
				(0.075)	(0.093)	(0.101)
Rho			**0.036**		**0.133****	**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.

In terms of the substantive interpretation of our covariates, Table 1 reveals several noteworthy findings. A higher proportion of women in legislative roles is consistently associated with fewer protests, suggesting that more representative institutions may mitigate the need for unconventional forms of political participation. By contrast, government ideology shows no significant effect on protest frequency. As expected, economic growth is linked to a decline in protests, likely reflecting fewer economic grievances during periods of prosperity. While there is some evidence that welfare spending reduces protests, this effect is not robust to the inclusion of country-level fixed effects. Additionally, we find no consistent effects for the GINI coefficient, unemployment, or economic openness, indicating that these economic factors do not appear to be direct drivers of protest activity once spatiotemporal dependencies are accounted for.

5. Conclusion

In this paper, we have analyzed the spatiotemporal dynamics of political protests in Europe using the novel STADL model. Our findings indicate significant spatial diffusion, as protests spread across neighboring countries even after accounting for alternative explanations. Additionally, we detect temporal dependence, with protest activity influenced by events from at least one year prior. The presence of both spatial and temporal dependencies enhances our understanding of the contagious nature of political protests.

To mitigate the risk of spurious inferences, we apply the STADL model, as recommended by Cook, Hays, and Franzese (2022) and Hays et al. (2022), to our cross-sectional time-series analysis. Our results provide key insights into protest diffusion dynamics and challenge claims that protests do not spread across time and space, supporting the view that mobilization is shaped by both past and proximate protests. The STADL model improves inference by incorporating both temporal and spatial lags, reducing bias in estimating the effects of covariates—an issue overlooked in previous studies, potentially leading to misleading conclusions.

Distinguishing and accurately estimating these dependencies is crucial for obtaining unbiased estimates of the structural factors driving protests, even when researchers are not primarily focused on the spatiotemporal process itself. For instance, our findings—such as the statistically insignificant effect of inequality on protest frequency—offer new empirical evidence that informs ongoing theoretical debates.

Our findings underscore the contagious nature of protests across time and space, with important implications for political behavior and political protests. We know from recent work on policy diffusion that leaders are attuned to what transpires abroad (Ezrow et al. 2021; Böhmelt et al. 2016; Juhl and Williams 2022). Our work suggests that activists and voters are as well when deciding when to engage in political protests. By learning from past events and the experiences of neighboring countries, leaders may take proactive measures to prevent protests from escalating. Addressing grievances early, implementing responsive policies, or making strategic concessions could help contain mobilization before it gains momentum.

Alternatively, governments in states that are experiencing democratic backsliding, such as Hungary, may seek to preempt mobilization based on signals from both abroad and past events. This could involve heightened surveillance and censorship, particularly when protests arise in neighboring countries or follow similar past incidents. As AI-powered monitoring advances, enabling real-time tracking and suppression of dissent, insights from both foreign protests and historical patterns may further incentivize the pernicious use of AI, such as facial recognition, and social media surveillance as tools of repression to curb protest diffusion (see Qin, Strömberg, and Wu 2017; Beraja et al. 2023).

Importantly, the findings from our study do not suggest that protests grow and spread indefinitely but rather follow cycles of mobilization, where waves eventually subside due to government responses, movement fatigue, or shifts in public sentiment. While our methods do not allow us to pinpoint precisely when protests begin to wane, anecdotal evidence suggests that they are neither perpetual nor capable of spreading boundlessly. At the core of our diffusion theory is the idea that past events and international developments shape future mobilization by signaling the effectiveness of protests and the potential for political change. Successful protests can trigger a chain reaction across time and space, inspiring further action. Conversely, repeated protests that fail to achieve tangible outcomes may signal the ineffectiveness of protest, discouraging future mobilization and diminishing the role of protest as a tool for political expression. Some work on participation does find that negative experiences with political participation can weaken the desire to engage again later (Franklin and Hobolt 2011). Future research should further explore how protest success influences diffusion and whether unsuccessful movements suppress subsequent mobilization in neighboring contexts.

Our study provides important evidence to the debate surrounding the contagious nature of protests by using novel spatiotemporal modeling techniques to gain better leverage on the mechanics of protest diffusion. Future research should further investigate how and why protests spread, both across time and between neighboring countries. Examining the roles of geographic proximity, communication channels, organizational networks, media consumption, and political attitudes, among other factors, will deepen our understanding of the underlying mechanisms driving diffusion. Moreover, studying protest diffusion beyond Europe—where border permeability, shared media access, and distinct diffusion dynamics may shape mobilization differently—would offer valuable comparative insights. Addressing these questions will advance knowledge on the transnational spread of social movements and the conditions that sustain their momentum.

6. Competing interests

The author(s) declare none.

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Online Appendix

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

1. Appendix containing the time dependence and intercept heterogeneity analysis.
2. Appendix containing the spatial dependence analysis for three and five neighbors.
3. Appendix with brief notes about model specification.

Appendix 1. Appendix containing the time dependence and intercept heterogeneity analysis.

See HTML.

Appendix 2. Appendix containing the spatial dependence analysis for three and five neighbors.

See HTML.

Appendix 3. Appendix with Brief Notes about 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.

Appendix 3.1 Temporal

Ljung-Box test We run a Ljung-Box test to analyze the relationship of the residuals.[9] 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.[10]

ACF and PACF tests Next, we conduct ACF and PACF tests (see details in 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 support for Hypothesi 1. Protests in one year appear to be a function of the number of protests from at least two years prior.

Appendix 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 Hypothesis 2. Thus, to understand protest we need to account for spatial dependence and use a Spatial Autocorrelation (SAC) model.

9. The full results are reported in the Appendix 1.
10. See also the residual plot reported in the appendix.

Appendix 3.3 Fixed or Random Effects

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.[11]

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