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Riding the Tide: How Online Activists Leverage Repression

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Abstract

How does repression reshape the way online activists engage with target audiences? While prior research has primarily examined changes in overall online participation, it has paid less attention to how activists adjust their strategies in response to repression. Addressing this gap, this article argues that repression incentivizes online activists to broaden their support base by promoting inter-group engagement and signaling inclusivity. Focusing on the 2011 Occupy Wall Street movement, the study analyzes Twitter interactions using network measures of assortativity and cross-group tie proportions. It applies permutation tests and ARIMA-based Interrupted Time Series (ITS) analysis to compare network patterns across key phases, delineated by the Brooklyn Bridge mass arrests on October 1 and the eviction threat of Zuccotti Park on October 13. The results show that repression triggers a significant decrease in assortativity, indicating increased inter-group engagement, while cross-group tie proportions remain stable, suggesting structural rather than isolated behavioral changes.

Keywords

online activism, repression, assortativity, cross-group communication, network analysis

Introduction

The rise of digital platforms has transformed the landscape of political activism, allowing protest movements to coordinate actions, amplify messages, and build solidarity across geographic and ideological boundaries. As online spaces have become central arenas for dissent, questions about how activists adapt their digital strategies in response to external pressures have gained growing scholarly attention. A notable early example of this shift was the 2011 Occupy Wall Street (OWS) movement, which emerged in New York City and rapidly spread across the globe through digital networks. Framing their struggle around the slogan “We are the 99%,” OWS activists mobilized against economic inequality and corporate influence, using platforms like Twitter to organize protests and communicate with both supporters and the broader public. The movement’s decentralized

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structure and heavy reliance on social media also made it a key site of contestation between activists and state authorities, with online and offline repression shaping the dynamics of engagement.

How does repression change the way online activists build their relationships with target audiences? While existing scholarship on digital activism has made important contributions, key dynamics remain underexplored. In particular, existing scholarship has largely focused on how regimes shape digital environments, often paying less attention to how online activists adjust their own strategies, especially in response to offline repression. This study addresses that imbalance by examining how activists recalibrate their online engagement, including visibility, coordination, and information flow, following episodes of offline repression.

In response to these underexplored dynamics, this article argues that repression reshapes how online activists cultivate relationships with their target audiences. Online activists seek to broaden the support base for the offline groups they advocate, aiming both to promote their agendas and prevent their marginalization within the movement. Consequently, they are incentivized to promote their groups to attract a wider audience of potential supporters. Repression functions as a catalyst for heightened public attention, prompting activists to actively engage in promotional efforts following major repressive events. In particular, they demonstrate inclusiveness and openness by making their interactions with other online protest groups more visible. As a result, online activists increasingly prioritize inter-group interactions, reflecting a strategic shift toward broader advertising efforts in response to repression. On the other hand, during inter-repression periods characterized by relative peace and reduced repression, online activists shift their focus toward consolidating internal cohesion and strengthening ties with their core audiences, leading to a halt in the increase of inter-group interactions.[1]

To test this argument, this article analyzes Twitter data generated during the 2011 Occupy Wall Street movement. Examining interactions between Twitter users is well-suited for this purpose, given the inherently public and communicative nature of tweet interactions: users engage with others' tweets to publicly signal their interest not only to their own supporters and the audiences of the users they engage with but also to the broader public. This study primarily employs network analysis, using nominal assortativity and cross-group tie proportions as main indicators of whether online activists prioritize interactions with different groups. To identify distinct grouping patterns among online activists, it applies Latent Dirichlet Allocation (LDA) topic modeling with Louvain and Leiden community detection algorithms. The analysis compares these indicators across different network phases, delineated by two major repressive events: the mass arrests on the Brooklyn Bridge on October 1 and the threat of eviction from Zuccotti Park on October 13. To conduct these comparisons, the study incorporates various techniques, including permutation tests and ARIMA-based Interrupted Time Series (ITS) analysis.

The analysis generally supports the proposed argument. Specifically, assortativity significantly decreases following the two repressive episodes, indicating a relative increase in inter-group interactions, while remaining stable during inter-repression periods. Cross-group tie proportions, however, do not exhibit significant changes. These findings suggest that the observed shifts after repressive events reflect broader structural and behavioral changes across the network, rather than being driven by a small number of highly active users. Overall, the results thus provide nuanced support for the article's hypotheses.

This article is structured as follows. First, it reviews existing research on the relationship between repression and online activism. The next section presents the article's main argument. After providing background on the Occupy Wall Street movement, the article outlines a set of predictions derived from its hypotheses. It then introduces the indicators used in the analysis, explains the group identification process, and describes the testing strategy based on permutation tests and Interrupted Time Series (ITS) analysis. The article concludes by summarizing the key contributions and implications of the study.

Current Debates on Repression and Online Activism

As the internet and online political participation have attracted growing scholarly attention (Honari, 2018a), repression studies have expanded to encompass both offline and online contexts. Offline repression has long been studied in relation to participation outcomes, with research emphasizing its deterrent, mobilizing, or structuring effects. Theories such as resource mobilization and collective action highlight how repression raises the costs of dissent, thereby reducing protest through organizational disruption or individual disincentives (Khawaja, 1993; Kitschelt, 1986; Lichbach, 1994; McCarthy & Zald, 1977; Oliver, 1980; Olson, 1971; Tilly, 1978; Zhukov, 2023). However, this cost-centric view has been challenged by findings that repression can also provoke mobilization when it generates emotional responses such as anger or moral outrage (Saab et al., 2015; Siegel, 2011), especially when perceived as illegitimate (Gurr, 1970). Scholars have also theorized non-linear relationships between repression and dissent, either inverted U-shaped, where extreme violence suppresses protest (Gurr, 1970), or backlash-driven, where high repression erodes fear and sustains resistance (Pearlman, 2013). Empirical studies further show that backlash is often conditional, depending on political context, movement structure, or protest form (Bell & Murdie, 2018; Finkel, 2015; R. Francisco, 2004; Parkinson, 2013; Sullivan & Davenport, 2017).

Beyond participation levels, repression also shapes how dissent is enacted. Scholars have documented shifts in tactics, organizational forms, and symbolic practices in response to coercion (Almeida, 2008; Arslanalp & Erkmen, 2025; Cunningham et al., 2017; Francisco, 1995, 1996; O'Brien & Deng, 2015). Activists may respond by moderating their behavior (Titarenko et al., 2001), reconfiguring their roles (Honari, 2018b; Honari & Muis, 2021; Reynolds-Stenson, 2022), or intensifying their claims and targeting new spaces of contestation (Honari & Muis, 2021; Kang, 2023; O'Hearn, 2009). Repression can also escalate dissent into violence under certain conditions (Araj, 2008; Lichbach, 1987; Moore, 1998; Ryckman, 2020; White, 1989).

Digital repression research builds on these insights but centers on how authoritarian regimes exploit new technologies to control online dissent. Earlier accounts viewed online repression mainly as a cost mechanism that discourages participation (Earl & Beyer, 2014; Honari, 2018b; Morozov, 2011). More recent work, however, highlights how regimes increasingly use surveillance, blackouts, and propaganda to manage dissent in targeted and strategic ways. Feldstein (2021) describes the growing sophistication of these tools across contexts such as Thailand, Ethiopia, and the Philippines, emphasizing how digital repression strategies are shaped by state capacity, leadership, and historical patterns of coercion. Gohdes (2015, 2020) finds that internet shutdowns coincide with spikes in violent repression, and that surveillance enables precision targeting of opposition, especially in contested areas. Xu (2021) similarly argues that digital surveillance solves dictators' information problems, facilitating selective repression over broad co-optation. Rød and Weidmann (2015) show that despite early hopes, internet expansion has not fostered democratization and may even entrench authoritarian control. Finally, Huang (2018) notes that hard propaganda can deter protest while also eroding regime legitimacy over time.

While these studies provide critical insights into state repression in digital environments, much less is known about how activists adapt their digital strategies in response. Existing work tends to emphasize what regimes *do* to online spaces, often overlooking how activists recalibrate their own practices, including information sharing, coordination, and visibility, especially in the aftermath of *offline* repression. This study addresses that gap by examining how online activists adjust their digital engagement in response to state crackdowns, highlighting the agency of dissenters operating across intertwined online and offline spheres. In doing so, it contributes to a more interactive and relational understanding of the repression–resistance nexus in the digital age.

Theory

Hypotheses

Protest groups participating in a movement typically pursue two main goals. First, as Beissinger (2013) notes, groups often join demonstrations not only to support the primary cause of the struggle but also to promote their own specific agendas. Protest movements frequently serve as umbrella spaces that bring together diverse actors, each with distinct priorities, identities, and grievances. For example, during the 2021 anti-coup protests in Myanmar, women's protest groups sought not only to resist military rule but also to challenge entrenched gender norms and promote greater gender equality (Lusan et al., 2021). This illustrates that participation in protest movements is often motivated by the dual imperatives of supporting a shared cause while simultaneously advancing group-specific missions. Maintaining a visible and independent agenda within the broader movement can help groups influence the movement's priorities and outcomes, ensuring that their unique concerns are not overshadowed by dominant factions.

Second, protest groups seek to avoid marginalization within the movement to fully exercise their agency. As Wood (2015) argues, the act of exercising agency—taking purposeful action toward one's goals—is a critical emotional and psychological motivator, even in contexts characterized by danger and uncertainty, such as violent conflict or authoritarian repression. Participation offers protesters a sense of dignity, empowerment, and emotional fulfillment, stemming from the ability to act rather than remain passive. However, internal marginalization within the movement can undermine these emotional payoffs. When groups feel sidelined or ignored, their members may experience frustration, disillusionment, or alienation, reducing both their emotional engagement and their willingness to sustain participation.

Securing a broad and loyal public support base is crucial for achieving both goals. Externally, a strong support base enables a protest group to amplify its agenda, shape public discourse, and gain bargaining power in interactions with state authorities or other political actors. Internally, public backing strengthens a group's standing within the broader movement, enhancing its influence in decision-making processes and reducing the risk of being marginalized. Thus, cultivating broad support sustains both outward impact and internal agency, reinforcing the group's ability to pursue its dual objectives over time.

Similar strategic dynamics are likely to emerge among online activists, even if they do not physically participate in protests. Online activists often closely identify with protest movements and, more specifically, with constituent groups whose agendas align with their concerns or identities. They seek the success of the movement as a whole but are also invested in ensuring that specific issues they care about are effectively represented and addressed. As such, online activism often involves not only promoting the broader movement but also advocating for particular group agendas within it.[2]

Like physical protest groups, online activists must manage two strategic imperatives: expanding their support base and retaining their core supporters. To broaden their audience, activists must increase the visibility of their agenda, often signaling openness to collaboration and solidarity with other groups. Cross-group engagement can make activists appear more inclusive, attract a wider range of supporters, and amplify their message across different social networks. However, to retain their foundational support base, activists must also signal loyalty to their core identity and principles, avoiding actions that might suggest excessive compromise or ideological dilution. Thus, activists operate under a fundamental tension: broadening the base often requires flexibility, while maintaining core loyalty demands steadfastness and ideological clarity.[3]

Given this tension, online activists tend to adopt risk-averse strategies when considering outreach beyond their core constituencies. They are cautious about diluting their identity or alienating their foundational supporters, who provide consistent emotional and logistical support. In the absence of clear strategic opportunities, the perceived costs of expansive outreach, such as internal fragmentation or loss of authenticity, typically outweigh the uncertain gains of attracting new supporters. As a result, online activists often maintain a relatively narrow focus, concentrating on reinforcing their core agendas until they perceive a favorable shift in external conditions. In other words, they tend to "strike only when the iron is hot." This aligns with Meyer (2004), who contends that activists' capacity to grow their movements, by advancing specific claims, mobilizing supporters, and exerting influence, is conditioned by the broader political opportunity structure.

Repressive events often create such moments. Graphic, violent, and emotionally charged images of repression can dramatically shift public attention, drawing in audiences who were previously disengaged or ambivalent. Repression can trigger widespread sympathy for the protest movement and mobilize latent supporters who might not have otherwise taken sides. However, this surge of attention does not automatically translate into support for specific groups within the movement. New audiences, lacking familiarity with the movement's internal dynamics, require signals and cues about which groups to support. Online activists often gauge these strategic moments by monitoring multiple cues in the digital environment, such as spikes in media coverage, trending hashtags, viral content, or sudden surges in engagement metrics. Because decisions to act rarely occur in isolation but instead emerge from interdependent dynamics within networks (González-Bailón et al., 2013), such signals can serve as cues that public attention has reached a critical threshold, making broader outreach more likely to succeed. Recognizing this opening, online activists may temporarily shift their strategies to emphasize cross-group engagement, projecting an image of inclusiveness and collective solidarity to appeal to the newly attentive public.[4]

Such strategic behavior allows activists to maximize the benefits of expanded public visibility while mitigating the risks associated with alienating existing supporters. By showcasing cross-group interactions during periods of heightened attention, activists position themselves as central and indispensable actors within the movement, increasing their chances of attracting new followers without immediately compromising their core identity. This pattern echoes prior findings that protest groups may temporarily overcome internal divisions and form new alliances under repressive pressure, either through strategic coordination or symbolic reframing of grievances (Chang, 2008; Osa, 2003).

However, this strategy is difficult to sustain once the immediate wave of public attention fades. As media coverage shifts away from the movement and audience engagement declines, online activists must refocus on consolidating their internal support base to prevent erosion of loyalty. They may retreat from overt cross-group signaling, reassert their foundational agendas, and invest in cultivating internal cohesion, particularly by integrating new recruits and reaffirming core principles. This cycle can repeat across multiple protest phases: during periods of heightened public attention triggered by repression, activists engage more broadly; during calmer periods, they turn inward to consolidate their base and preserve their distinct identity.

Thus, this study expects a dynamic pattern in online activist interactions, reflecting cycles of external attention and internal consolidation.

> **Hypothesis 1.** The presentation of interactions between different online activist groups tends to increase following major repressive events, as activists seek to broaden their support base during windows of heightened public attention.

> **Hypothesis 2.** The presentation of interactions between different online activist groups tends to stabilize or decline after the initial surge, as activists refocus on consolidating internal cohesion until another major repressive event occurs.

Predictions from Occupy Wall Street Movement

The Occupy Wall Street movement began on September 17, 2011, in Zuccotti Park in New York City, led by the Canadian activist group Adbusters. It drew participants from diverse political, racial, and gender backgrounds. Framing themselves as the "99%," protesters opposed the greed, corruption, and social control of the wealthiest 1%. Their demands included better job opportunities, fair income distribution, banking reforms, and reduced corporate influence in politics. The movement used nonviolent tactics inspired by the Arab Spring to achieve its goals and ensure participant safety (Yangfang, 2012).

Occupy Wall Street is selected as the main case for four key reasons. First, the movement is relatively typical in terms of repression intensity. The types and levels of repression during Occupy Wall Street were moderate compared to other movements. Arrests, a common and less severe form of repression (Earl, 2011), were widely used, and police violence remained nonfatal. Second, the movement's global significance makes it worth studying. Occupy Wall Street inspired similar occupations in over 15 countries across Australia, Asia, Europe, and the Americas (L. G. E. Smith et al., 2015). As one of the earliest and most notable protests, it holds particular importance. Third, the movement's decentralized structure highlights the role of informal connections among participants (Savio, 2015), through which protest groups coordinate and exchange information. These informal ties facilitate cross-group communication in the absence of centralized leadership, making the movement an ideal case for testing hypotheses about how online activists present their interactions to broader audiences. Last but not least, the case offers an abundance of data for analysis. Occupy Wall Street saw extensive activity on Twitter (Penney & Dadas, 2014), providing valuable information to study online activists' interactions.

There were two major repressive events during the movement: the mass arrest of approximately 700 protesters on the Brooklyn Bridge on October 1, and the threat of eviction from Zuccotti Park on October 13. Although the clearance of the park was ultimately called off at the last minute, it drew substantial public attention and posed a serious threat that could have brought the occupation to an end. Given the heightened public attention surrounding these repressive events, online activists are expected to make strategic efforts to expand their support base by visibly engaging with other online groups in the aftermath.

Prediction 1: Immediately following October 1 and October 13, online activists are more likely to display interactions with one another.

Following each surge in the presentation of inter-group interactions, online activists are likely to return to a more stable pattern, shifting their focus toward strengthening intra-group cohesion.

Prediction 2: Following the rise in inter-group interaction displays after October 1, online activists will maintain a steady level of such displays until October 13.

Research Design

Data

To test the hypotheses and specific predictions, the article primarily relies on network analysis, which can be a useful tool to effectively examine interdependent dynamics of influence among relevant actors (Hafner-Burton et al., 2009; Ward et al., 2011). Network analysis offers a complementary approach to operationalizing the concepts of existing theories, allowing for more direct and precise indicators of these concepts. For example, Zech and Gabbay (2016) demonstrate that in the context of militant fragmentation, the level of institutionalization, as proposed by Bakke et al. (2012) as one of the three variables of fragmentation, can be more effectively quantified using network density.

The article employs Twitter users related to the Occupy Wall Street movement as the primary data source. It focuses on self-reported Twitter users from New York, despite the challenge that geolocation data from tweets is not representative of the U.S. population (Malik et al., 2021). According to Penney and Dadas (2014), the vital role of "internetworked" peer-to-peer communication has been evident in the development of the movement. Twitter has played a notable role in facilitating the continuous sharing and amplification of information about the movement among users from diverse locations, being a privileged tool for constructing horizontal networks of exchange. The article includes all types of Twitter interactions in the analysis, such as retweets, replies, and likes, as all of them can publicly display both the sender and the recipient.

Twitter interactions between different online activist groups serve as a direct indicator of communicative presentation, reflecting the groups' intent to signal inclusiveness to public audiences. While these interactions may not reflect actual or in-person collaboration, this is not a limitation for the purpose of this study. Twitter activity is inherently public and designed to convey information, making it a form of advertisement. Therefore, whether the interactions represent real coordination is less important than their function as visible signals.

The analysis seeks to assess how patterns of Twitter interactions shift in response to repressive events by comparing the movement's dynamics before and after each episode of repression. It begins by transforming Twitter users exhibiting activities between September 17 and October 31 into undirected network data. The network is segmented into three phases, using the mass arrests on the Brooklyn Bridge on October 1 as the first dividing point and the threat of eviction from Zuccotti Park on October 13 as the second. The analysis includes Twitter users who were active between September 17 and October 31 and who appeared in all three network phases. This sampling strategy focuses on sustained participants in the Occupy Wall Street conversation, allowing for consistent comparison of interaction patterns across periods. While this approach excludes users who joined the conversation after each repressive event, potentially omitting interactions between new and existing users, it helps isolate the behavioral shifts among consistently present actors without introducing confounding variation driven by user turnover. This trade-off prioritizes internal validity over representativeness, which is common in studies comparing network dynamics before and after interventions (e.g., Prochnow et al., 2022). The resulting network contains 1,835 nodes (users) and 676, 1,105, and 1,340 edges (interactions) in each respective phase.

Indicators

Assortativity. The article primarily uses assortativity measures to assess how interaction patterns among Twitter users shift following repression. Assortativity is an empirical measure that captures the positive correlation between the traits or personal attributes of individuals who are socially connected, such as age, education, socio-economic status, physical appearance, or religion. For instance, in the case of socio-economic status, a community is considered assortative if individuals with similar socio-economic backgrounds are more likely to be friends than two randomly chosen individuals (Buccafurri et al., 2015). In essence, assortativity reflects the degree of homophily, the tendency for individuals or entities to associate with others who share similar characteristics (McPherson et al., 2001). Assortativity for nominal attributes is calculated using the following formula (Newman, 2002):

$$r = \frac{\sum_i e_{ii} - \sum_i a_i^2}{1 - \sum_i a_i^2}$$

Here, e_{ii} represents the fraction of edges that connect nodes of the same category i, and a_i denotes the fraction of all node ends that belong to category i. The numerator measures the difference between the observed proportion of same-category connections and the expected proportion under random mixing. The denominator normalizes this difference by the maximum possible value, ensuring that r ranges between -1 and 1. A positive r indicates assortative mixing (preference for similar nodes), whereas a negative r indicates disassortative mixing (preference for different nodes).

To calculate nominal assortativity, each Twitter user must be assigned a specific attribute or category, such as ideological stance or group membership. Without assigning users to identifiable groups, it becomes impossible to assess whether interactions are occurring preferentially among similar individuals, which is the core of what assortativity captures. Accordingly, this study constructs assortativity measures by assigning two distinct types of attributes to Twitter users. First, to approximate the formal and informal online group affiliations of Twitter users, the study applies the Louvain community detection algorithm.[5] In the context of the present study, communities refer to clusters of Twitter users who exhibit stronger connections with each other compared to users outside of those specific groups. Communities thus can represent relatively exclusive patterns of interaction between users, thereby capturing rough boundaries of formal and informal online activist groups. Indeed, studies have evidenced that communities represent meaningful organizational units and offer novel insights into the structure and functioning of the entire network under examination (Papadopoulos et al., 2012). Hence, the community assortativity term quantifies the extent to which Twitter users are more likely to form or maintain connections with others who belong to the same detected community. A positive assortativity coefficient indicates that users preferentially interact within their own community, while a negative value would suggest more cross-community interaction.

While the widely used Louvain community detection method is utilized for generating the community assortativity term, it is worth noting that there exist many other community detection methods that could be employed by researchers (Smith et al., 2020). Each of these detection methods follows distinct processes, thereby compensating for the disadvantages of one another and providing complementary approaches. According to Traag et al. (2019), the Louvain community detection may find badly connected communities in an arbitrary manner. Specifically, they demonstrate that the Louvain algorithm tends to identify communities that exhibit internal disconnection. Within these communities, there are situations where certain parts can only be reached from other parts by traversing paths that extend beyond the boundaries of the community. As an alternative to the Louvain algorithm, Traag et al. (2019) introduce the Leiden community detection, which ensures that communities are adequately connected. To address the possible effect of different community detection methods on the results, the article implements another model employing the homophily term based on the Leiden algorithm.

The second type of assortativity term is created utilizing the Latent Dirichlet Allocation technique, which can identify distinct topics from a given corpus of documents. Topic numbers generated by the LDA model are assigned to each Twitter user according to the content of their tweets, allowing the analysis to capture their varying interests in prominent topics or discussions.[6] The topic assortativity term generated through this process quantifies the degree to which Twitter users who share similar topical interests are more likely to interact with one another. A higher topic assortativity value indicates that users with shared interests are forming or maintaining connections at a rate greater than would be expected by chance, while a lower or negative value suggests more cross-topic interaction or a lack of topical clustering in the network.[78] Figure 1 illustrates the daily trend of assortativity, showing sharp declines that become particularly evident following the two repressive events.

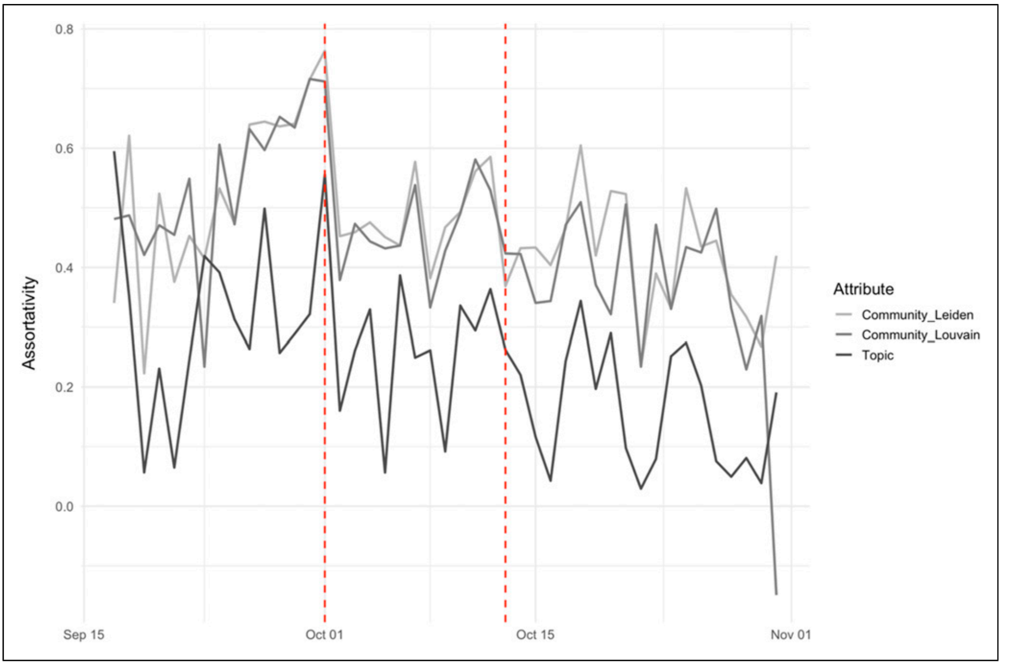

Figure 1. Daily Trend of Assortativity

Cross-Group Tie Proportion. The proportion of cross-group ties is examined as a complement to the assortativity measure. It is calculated as the number of ties between nodes with different attribute values divided by the total number of ties in the network. The benefit of using this indicator is twofold. First, as a complementary measure, it helps assess the robustness of the analysis. Second, because it captures a different dimension of network structure than assortativity, it enables more nuanced interpretations. Figure 2 shows the daily trend in the proportion of cross-group ties, with noticeable increases that become especially pronounced after the two repressive events. Although the topic-based trend declines following the eviction threat on October 13, the other indicators generally exhibit an upward shift immediately after the repressive events.

While both assortativity and the proportion of cross-group ties aim to capture inter-group interaction within a network, they reflect different aspects. Assortativity is sensitive to both the density of within-group ties and the relative balance between internal and external connections. In contrast, the proportion of cross-group ties is a more straightforward, descriptive measure that captures the share of all connections that occur between nodes with different group labels. This measure does not account for how clustered or those ties are, nor does it capture the internal cohesion of groups.

Comparing Between Phases

This study examines changes in assortativity and the proportion of cross-group ties before and after the two repressive events and analyzes their overall trend. The two assortativity measures—community and topic—are expected to decline from the first phase to the third phase, as the network undergoes two episodes of repression. The decrease in assortativity indicates that Twitter users from different online protest groups are less likely to interact exclusively within their own groups and more likely to engage across group boundaries through retweets, replies, and likes.

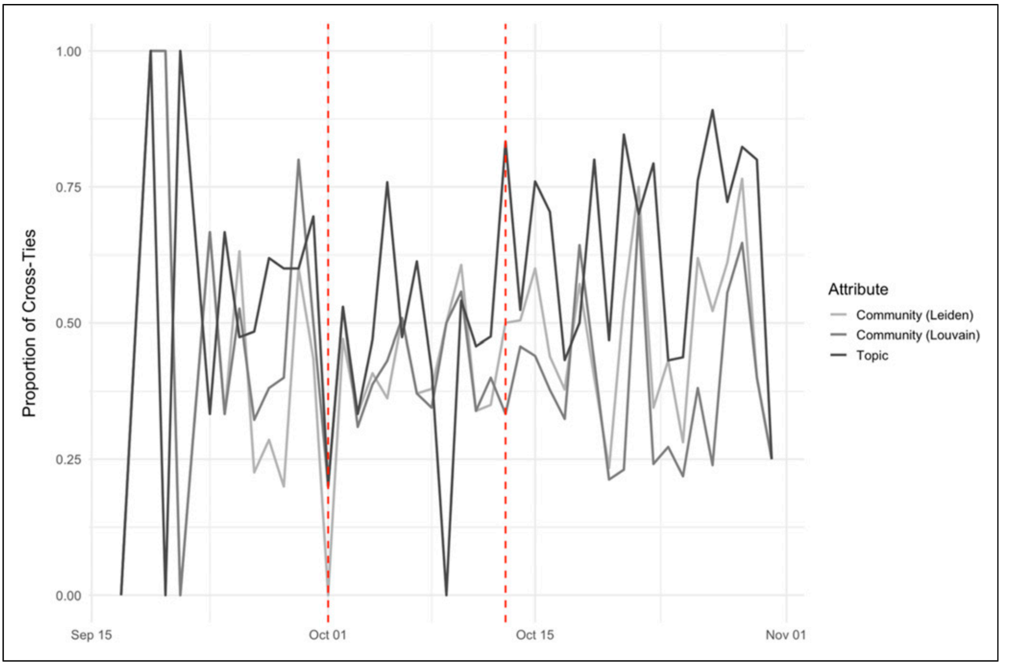

Figure 2. Daily Trend of Proportion of Cross-Group Ties

Similarly, users with diverse topical interests appear to interact more frequently beyond their primary topic clusters. On the other hand, the two proportion measures are expected to increase as the phases progress. An increase in these measures simply indicates that the share of inter-group ties is higher than in the previous phase.

To evaluate whether the observed differences in assortativity and cross-group tie proportions between the two network phases are statistically significant, a permutation test is performed. After calculating the observed values of each indicator based on node attributes, the attribute labels are pooled, randomly shuffled, and reassigned to nodes in the two networks while preserving the original group sizes. This procedure is repeated 1,000 times to construct a null distribution of indicator differences. The P-value is then computed as the proportion of permutations in which the permuted difference equals or exceeds the observed difference.

This permutation also addresses the possibility that the observed structural changes are merely artifacts of shifts in group size composition rather than genuine changes in connection patterns. For example, consider a situation where a basket initially contains five apples and five bananas but later shifts to two apples and eight bananas. Even if fruits are paired randomly, the probability of forming an apple-apple pair would naturally decrease simply due to the smaller number of apples. Similarly, in a network, changes in the relative size of groups could affect assortativity or cross-group tie proportions without any true change in linking behavior. The permutation procedure adopted by this article ensures that any variation in the null distribution arises solely from the fixed composition of groups, by randomizing group labels while maintaining the original number of nodes assigned to each group. Consequently, if the observed difference exceeds the range expected under random assignment, it suggests that the structural changes are unlikely to be explained by compositional shifts alone, providing stronger evidence for substantive behavioral or organizational changes in the network.

Null Phase Permutation Test

A phase randomization test is conducted to evaluate the robustness of the observed network changes across protest phases. This simulation serves two main purposes. First, it tests whether the observed changes of the indicators exceed the level of variation one would expect from arbitrary temporal segmentation. In other words, it assesses the possibility that the observed shifts are merely artifacts of how the phases are defined. Second, the simulation addresses the concern whether the network's structural changes could have emerged naturally over time, regardless of any external shocks such as repression.

The simulation randomly selects two cut-points within the observed time range to divide the data into three phases of different lengths. For each simulated set of phases, both the assortativity and the cross-group tie proportion are recalculated using the same procedures as applied to the actual phases. This process is repeated 1,000 times to generate null distributions of phase-to-phase differences (Phase 2 minus Phase 1 and Phase 3 minus Phase 2) for each indicator. The observed differences from the actual repression-based phase segmentation are then compared against these null distributions. P-values are computed as the proportion of simulated differences that equal or exceed the observed value, indicating whether the actual network changes are significantly greater than what would be expected under random temporal segmentation. Statistically significant results will suggest that the observed structural shifts are unlikely to be due to arbitrary cut-points or natural evolution of protest networks, and instead suggest a meaningful change associated with the timing of repression.

Interrupted Time Series Analysis

The study also utilizes Interrupted Time Series (ITS) analysis to assess the impact of the two repressive episodes, as interventions, on subsequent levels of assortativity and the proportion of cross-group ties. ITS is valuable because it captures both the immediate impact of interventions and the subsequent trend during the post-intervention period. The study specifically employs an Autoregressive Integrated Moving Average (ARIMA) model to conduct ITS and extract the coefficients. ARIMA is useful for this analysis because assortativity and cross-group tie proportions are likely time-dependent and may exhibit autocorrelation, suggesting that their values at any given time are statistically influenced by preceding periods. By accounting for this temporal structure, the ARIMA model enables a more precise estimation of intervention effects.

Results

Figures 3 and 4 illustrate the temporal trends in assortativity and the proportion of cross-group ties. As shown in Figure 3, all assortativity measures exhibit a gradual decline as the movement passes through two episodes of repression. In contrast, Figure 4 illustrates that cross-group tie proportions generally increase over successive phases, although the communities identified by the Leiden algorithm exhibit a slight decline from Phase 2 to Phase 3. These patterns are thus consistent with the expectations derived from Hypothesis 1.

Table 1 presents the results of the permutation test for differences in assortativity. All differences in assortativity are negative, indicating a decline in assortativity compared to the previous phase. Although the change in topical assortativity between the first and second phases is not statistically significant, all other differences are highly significant. These results suggest that assortativity consistently decreases as the movement experiences major repressive events, providing general support for Hypothesis 1.

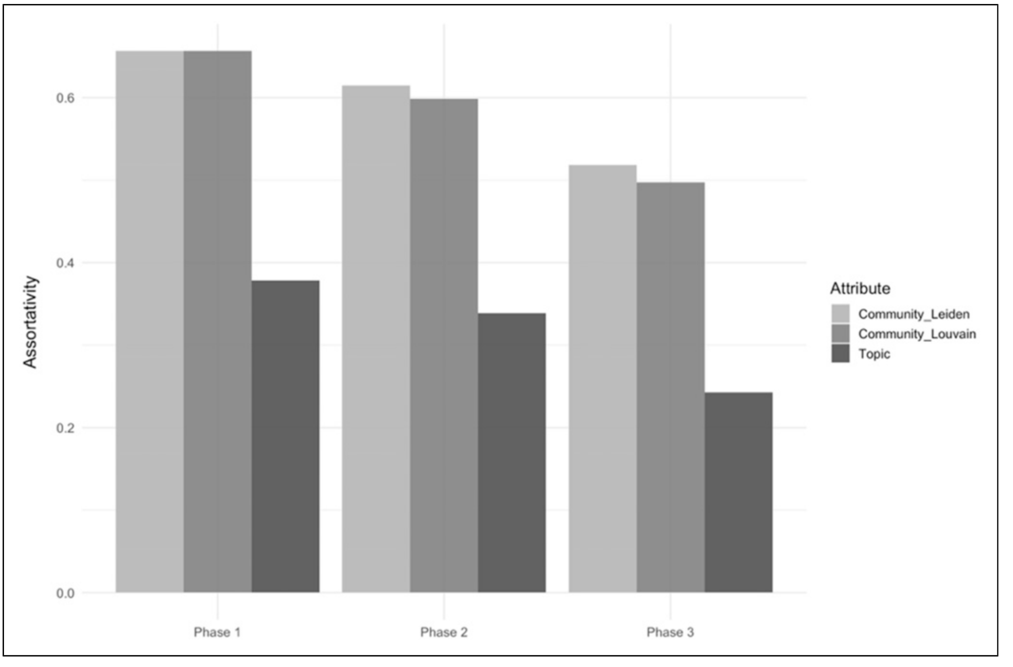

Figure 3. Assortativity Trend by Phases

Table 2 reports the results of permutation tests for differences in the proportion of cross-group ties between phases. Unlike the permutation test results for assortativity, this table mostly shows statistically insignificant differences, with some differences taking negative values. Therefore, although the proportion of cross-topic ties between the second and third

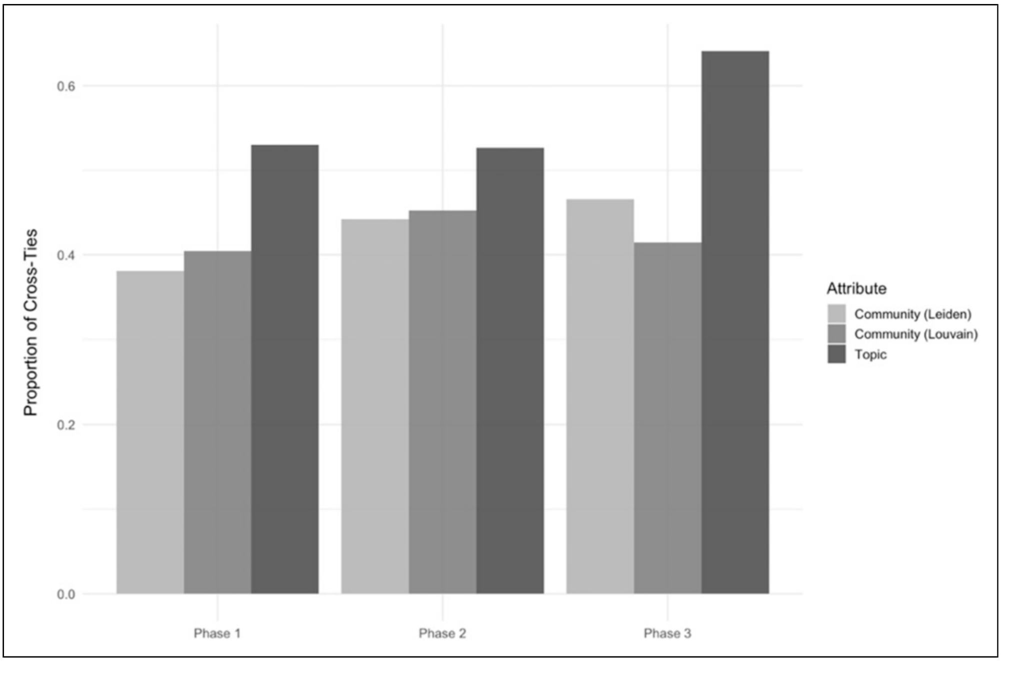

Figure 4. Cross-Group Tie by Phases

Table 1. Permutation Test Results for Assortativity

Phase comparison	Attribute	Pre	Post	Diff	P-value	Significance
Phase 1 vs Phase 2	Topic	0.378	0.371	−0.007	0.862	Insignificant
Phase 1 vs Phase 2	Community (Louvain)	0.656	0.546	−0.111	0.000	***
Phase 1 vs Phase 2	Community (Leiden)	0.656	0.568	−0.088	0.000	***
Phase 2 vs Phase 3	Topic	0.339	0.243	−0.095	0.000	***
Phase 2 vs Phase 3	Community (Louvain)	0.598	0.497	−0.101	0.000	***
Phase 2 vs Phase 3	Community (Leiden)	0.615	0.518	−0.097	0.000	***

Note. *P*-values are from permutation tests. ***$p < 0.001$.

phases reaches statistical significance, the overall findings offer only limited support for Hypothesis 1.

The mixed results call for further interpretation. The apparent discrepancy between assortativity and the proportion of cross-group ties may arise from the fundamental differences in what each metric captures. The proportion of cross-group ties is sensitive to the absolute number of cross-group connections, meaning that even a small number of highly connected nodes forming ties across groups can cause the metric to rise substantially. In contrast, assortativity reflects the overall tendency of nodes to connect with others sharing the same attribute, relative to the distribution of connections across the entire network. It thus captures how broadly and evenly inter-group ties are distributed rather than how many such ties simply exist. Given this distinction, the observed pattern suggests that changes in network structure are not driven by a handful of active connection makers. Instead, the assortativity shift implies a broader behavioral shift, where many nodes reduce their preference for within-group interaction. This interpretation supports the idea that the network's structural response to repression involves widespread behavioral changes, thus lending nuanced support to Hypothesis 1.

Figure 5 presents illustrative toy networks demonstrating how assortativity can decline while the proportion of cross-group ties remains constant. Both networks contain 10 nodes, and the left network represents the initial state, while the right network depicts the state after the change. As shown in the figure, assortativity declines sharply from 0.67 to −0.12, while the proportion of cross-group ties remains relatively stable, shifting only slightly from 0.17 to 0.22. In the initial network, inter-group ties are concentrated among a few nodes, whereas in the changed network, these ties are more evenly distributed across multiple actors in group A. Although group B's inter-group connectivity is concentrated in a single node due to its small size, the decrease in assortativity primarily reflects a broader shift in group A's behavior. Several nodes in group A now engage in cross-group connections, indicating a systemic move away from within-group

Table 2. Permutation Test Results for Cross-Group Tie Proportion

Phase comparison	Attribute	Pre	Post	Diff	P-value	Significance
Phase 1 vs Phase 2	Topic	0.530	0.527	−0.004	0.984	Insignificant
Phase 1 vs Phase 2	Community (Louvain)	0.404	0.453	0.048	0.587	Insignificant
Phase 1 vs Phase 2	Community (Leiden)	0.381	0.442	0.062	0.313	Insignificant
Phase 2 vs Phase 3	Topic	0.527	0.641	0.114	0.000	***
Phase 2 vs Phase 3	Community (Louvain)	0.453	0.414	−0.038	0.153	Insignificant
Phase 2 vs Phase 3	Community (Leiden)	0.442	0.466	0.023	0.599	Insignificant

Note. *P*-values are from permutation tests. ***$p < 0.001$.

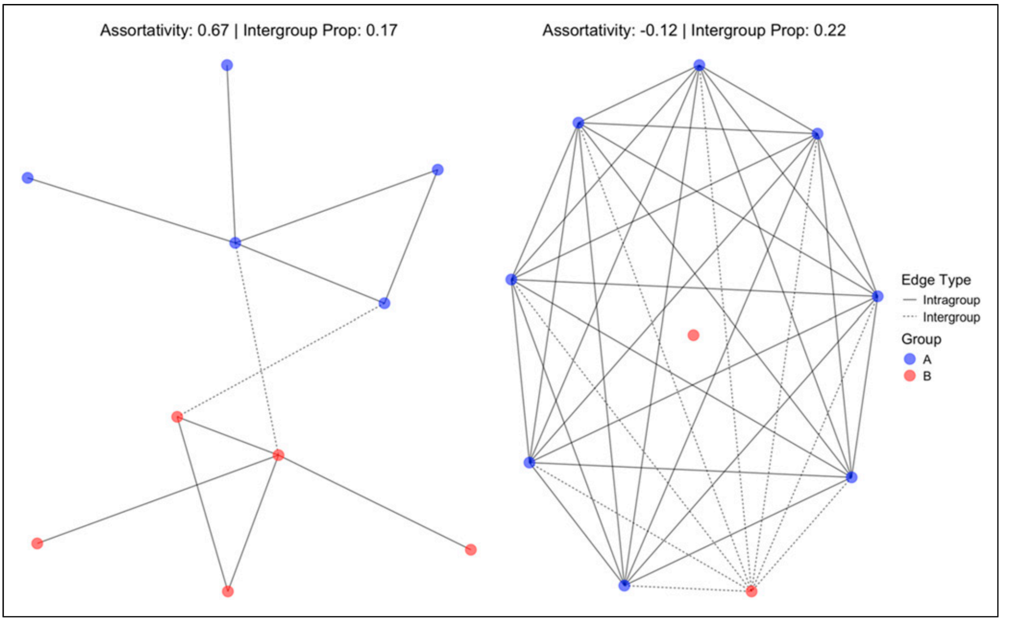

Figure 5. Toy Network: Assortativity and Cross-Group Tie Proportion Change

preferences. The decrease in assortativity thus reflects a broader structural shift in the network, indicating that the decline in homophily stems from more widespread changes.

Figures 6 and 7 depict where the observed differences fall within the distribution of differences generated under randomized phase assignments, testing the null hypothesis that these differences are not greater than what would be expected by chance. Figure 6 reveals that the observed differences in assortativity, which are highlighted by red lines, based on phase boundaries marked by the Brooklyn Bridge mass arrests and the Zuccotti Park eviction threat fall at the tails of the null distributions. Also, Table 3 shows that all observed values are statistically significant when compared to the null distribution. These results thus indicate that observed differences are unlikely to arise from arbitrary segmentation or natural evolution of the network. Together with the permutation test results shown in Table 1, this finding provides further support for Hypothesis 1.

In contrast, Figure 7 shows that although two observed differences lie at the extremes of the null distributions, the other four are located closer to the center. Indeed, Table 4 shows that only two differences are statistically significant. The lack of statistical significance in most comparisons suggests that the observed differences may not reflect meaningful structural shifts but could instead arise from the choice of temporal cut-points or inherent trends in the network's evolution. Considered alongside the largely insignificant differences reported in Table 2, this result suggests that the observed differences in cross-group interactions are more likely attributable to chance than to substantive structural change.

Figure 8 displays the fitted values from the ARIMA ITS model for assortativity. It shows that immediately following the interventions on October 1 and 13, assortativity sharply declines. In contrast, during the inter-repression period (Phase 2), the slope trends slightly upward but remains largely stable. This visual pattern is supported by Table 5, which presents the ITS coefficients and their statistical significance. Both intervention points (Phase 1 End and Phase 2 End) have negative and statistically significant coefficients, supporting Hypothesis 1 that assortativity decreases following repressive events. Conversely, the post-intervention trend coefficients (Time After

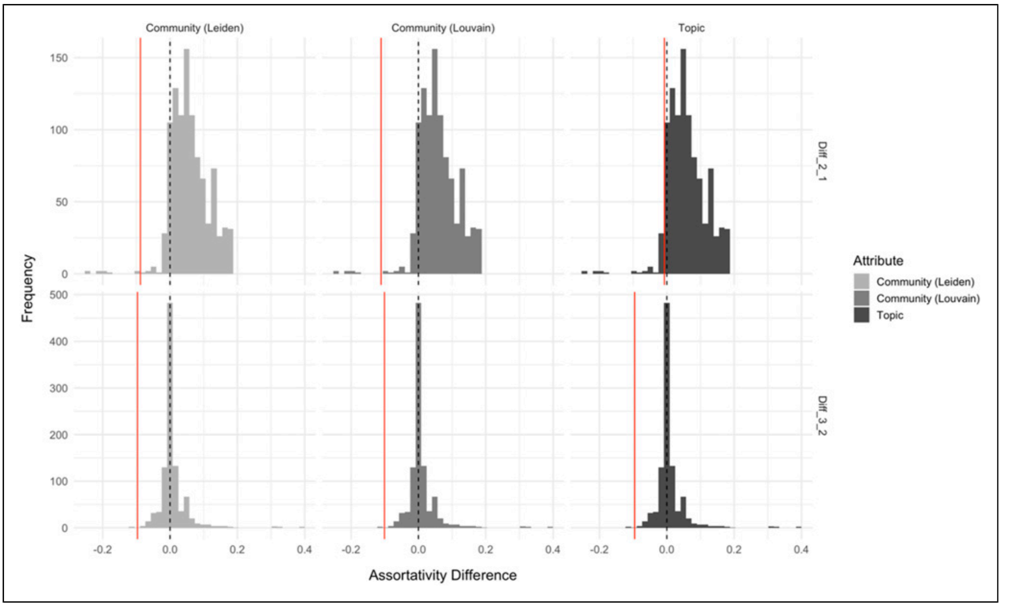

Figure 6. Observed Differences Compared to Null Distribution

Phase 1 and Time After Phase 2) are generally insignificant, except for the Topic-based trend after Phase 1. This suggests that during inter-repression phases, online activist groups neither substantially increase nor decrease cross-group communication, aligning with Hypothesis 2, which anticipates stability in these periods.

Figure 9 presents the fitted values from the ARIMA ITS model for cross-group tie proportions. Following the interventions on October 1 and 13, there is a tendency for cross-group ties to

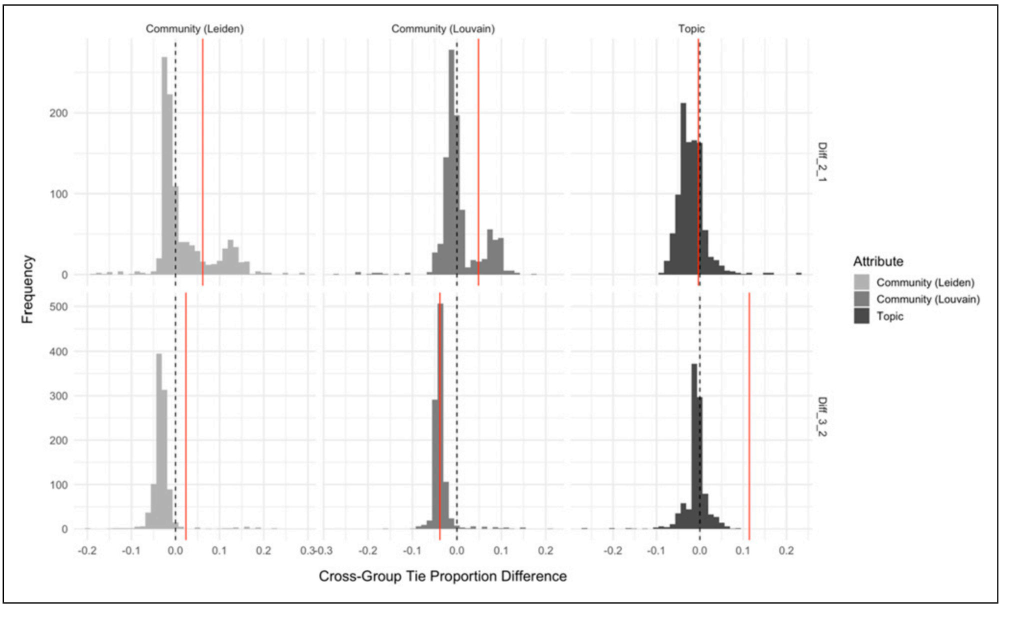

Figure 7. Observed Differences Compared to Null Distribution

Table 3. Permutation Phase Test Results for Assortativity

Phase comparison	Attribute	Difference	P-value	Significance
Phase 1 vs Phase 2	Topic	−0.007	0.049	**
Phase 1 vs Phase 2	Community (Louvain)	−0.111	0.007	***
Phase 1 vs Phase 2	Community (Leiden)	−0.088	0.009	***
Phase 2 vs Phase 3	Topic	−0.095	0.002	***
Phase 2 vs Phase 3	Community (Louvain)	−0.101	0.002	***
Phase 2 vs Phase 3	Community (Leiden)	−0.097	0.002	***

Note. *P*-values are from permutation tests. ***p < 0.001, **p < 0.05.

increase. On the other hand, during the inter-repression period (Phase 2), the trend remains largely stable. Table 6, which reports the ITS coefficients and their statistical significance, summarizes this visual pattern. While both intervention points (Phase 1 End and Phase 2 End) yield positive coefficients consistent with Hypothesis 1, they do not achieve conventional levels of statistical significance. This aligns with the earlier permutation tests, which also showed that cross-group tie proportions did not differ significantly from the simulated null distribution. Similarly, the post-intervention trend coefficients (Time After Phase 1 and Time After Phase 2) are generally insignificant, with the exception of the Louvain community trend following Phase 1. These findings support Hypothesis 2, indicating that cross-group communication remains relatively stable during inter-repression periods.

In sum, the findings provide nuanced support for the proposed hypotheses. When assortativity is used as an indicator of heterophily among Twitter users, Hypothesis 1 is strongly supported. The alignment between permutation tests and ARIMA ITS results suggests that the observed changes are unlikely to be driven by random variation, arbitrary network segmentation, or organic network evolution alone. In contrast, when the proportion of cross-group ties is used as the indicator, the estimates mostly fail to reach statistical significance, although their directional trends remain consistent with Hypothesis 1. This discrepancy does not necessarily weaken the hypothesis, as the two indicators reflect different dimensions of heterophily. Rather, the results suggest that the differences between phases may reflect broad shifts in user behavior across the network, rather than changes driven by a small number of users forming cross-group ties. Accordingly, the mixed findings may be interpreted as evidence of more systemic behavioral change across phases.

The empirical patterns also align with Hypothesis 2, which posits stable heterophilous interactions during inter-repression periods. Although this is essentially a support for a null finding, which is often interpreted with caution due to concerns about limited statistical power or measurement imprecision, the absence of statistically significant change in this context likely

Table 4. Permutation Phase Test Results for Cross-Group Tie Proportion

Phase comparison	Attribute	Difference	P-value	Significance
Phase 1 vs Phase 2	Topic	−0.004	0.239	Insignificant
Phase 1 vs Phase 2	Community (Louvain)	0.048	0.185	Insignificant
Phase 1 vs Phase 2	Community (Leiden)	0.062	0.206	Insignificant
Phase 2 vs Phase 3	Topic	0.114	0.000	***
Phase 2 vs Phase 3	Community (Louvain)	−0.038	0.346	Insignificant
Phase 2 vs Phase 3	Community (Leiden)	0.023	0.023	**

Note. *P*-values are from permutation tests. ***p < 0.001, **p < 0.05.

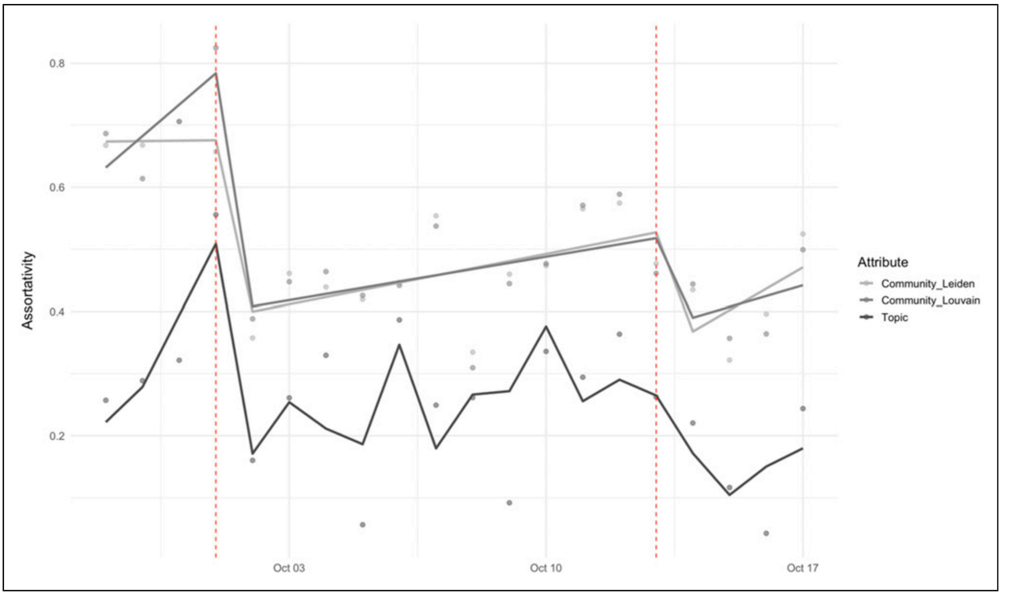

Figure 8. ARIMA-Fitted Interrupted Time Series: Assortativity

reflects a genuine structural stability in inter-group communication. As Wozniak et al. (2020) argue, null findings should not be dismissed as analytic failures. Rather, when interpreted through a clear theoretical lens, they may indicate the resilience of deeply held orientations or the structural persistence of interaction patterns. Accordingly, this null finding could be interpreted as theoretically meaningful.

Table 5. ARIMA ITS Results for Assortativity

Term	Attribute	Estimate	Std. error	P-value	Significance
Intercept	Topic	0.215	0.049	0.000	***
Intercept	Community (Louvain)	0.632	0.051	0.000	***
Intercept	Community (Leiden)	0.674	0.046	0.000	***
Time	Topic	0.086	0.027	0.002	**
Time	Community (Louvain)	0.051	0.027	0.061	Insignificant
Time	Community (Leiden)	0.001	0.024	0.978	Insignificant
Phase 1 End	Topic	−0.343	0.080	0.000	***
Phase 1 End	Community (Louvain)	−0.426	0.081	0.000	***
Phase 1 End	Community (Leiden)	−0.277	0.073	0.000	***
Time After Phase 1	Topic	−0.078	0.027	0.004	**
Time After Phase 1	Community (Louvain)	−0.041	0.028	0.138	Insignificant
Time After Phase 1	Community (Leiden)	0.011	0.025	0.661	Insignificant
Phase 2 End	Topic	−0.160	0.060	0.007	**
Phase 2 End	Community (Louvain)	−0.138	0.063	0.028	*
Phase 2 End	Community (Leiden)	−0.171	0.057	0.003	**
Time After Phase 2	Topic	−0.015	0.028	0.591	Insignificant
Time After Phase 2	Community (Louvain)	0.007	0.028	0.789	Insignificant
Time After Phase 2	Community (Leiden)	0.023	0.025	0.359	Insignificant

Note. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

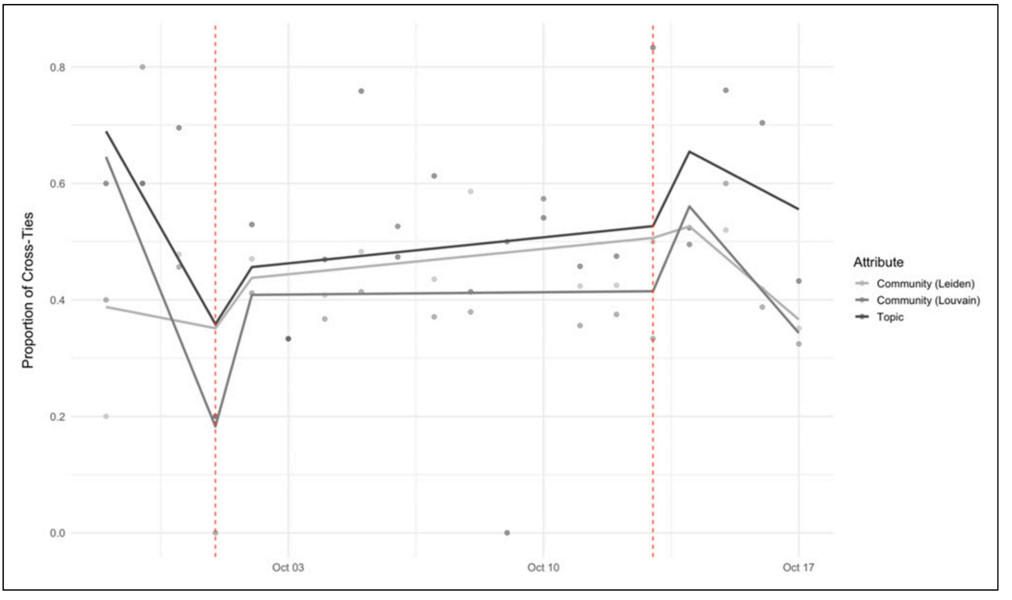

Figure 9. ARIMA-Fitted Interrupted Time Series: Cross-Group Tie Proportions

Alternative Explanations

One might argue that the observed patterns are not driven by online activists' efforts to promote protest groups aligned with their own concerns but rather by a broader attempt to strengthen the overall cohesion of the movement. However, if the increased inter-group communication were

Table 6. ARIMA ITS Results for Cross-Group Tie Proportions

Term	Attribute	Estimate	Std. error	P-value	Significance
Intercept	Topic	0.690	0.148	0.000	***
Intercept	Community (Louvain)	0.646	0.101	0.000	***
Intercept	Community (Leiden)	0.388	0.079	0.000	***
Time	Topic	−0.110	0.079	0.163	Insignificant
Time	Community (Louvain)	−0.154	0.054	0.004	**
Time	Community (Leiden)	−0.012	0.042	0.772	Insignificant
Phase 1 End	Topic	0.209	0.237	0.379	Insignificant
Phase 1 End	Community (Louvain)	0.380	0.161	0.018	*
Phase 1 End	Community (Leiden)	0.099	0.126	0.433	Insignificant
Time After Phase 1	Topic	0.117	0.081	0.147	Insignificant
Time After Phase 1	Community (Louvain)	0.155	0.055	0.005	**
Time After Phase 1	Community (Leiden)	0.018	0.043	0.667	Insignificant
Phase 2 End	Topic	0.122	0.184	0.508	Insignificant
Phase 2 End	Community (Louvain)	0.145	0.125	0.246	Insignificant
Phase 2 End	Community (Leiden)	0.014	0.098	0.889	Insignificant
Time After Phase 2	Topic	−0.039	0.081	0.624	Insignificant
Time After Phase 2	Community (Louvain)	−0.073	0.055	0.182	Insignificant
Time After Phase 2	Community (Leiden)	−0.060	0.043	0.164	Insignificant

Note. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

primarily aimed at promoting overall cohesion within the movement, it would require coordinated efforts across multiple online activist groups. Such coordination faces a classic collective action problem: achieving movement-wide cohesion would demand strong centralized leadership or a shared incentive structure among diverse groups. If only one group initiates efforts to build inter-group ties while others focus solely on their internal networks, the benefits of increased visibility would still be conferred to the broader movement. In that case, it would be more rational for most groups to free ride on others' efforts rather than invest in outreach themselves. However, the Occupy Wall Street movement was characterized by its decentralized, leaderless structure, which made it particularly difficult to overcome collective action problems. Therefore, it is more plausible to interpret the observed patterns as the result of individual activist groups pursuing rational, self-interested strategies.

Alternatively, one might argue that the observed patterns reflect increased cohesion and blurred group boundaries within the physical protest as a result of repression. However, without clear evidence that offline dynamics directly influenced online behavior, attributing changes in online interactions to on-the-ground structural shifts remains speculative and rests on an overly strong assumption.

Another possible alternative explanation is that increased media coverage following repression may independently stimulate cross-group engagement by drawing broader public attention to the movement. However, this possibility is not necessarily at odds with the article's theoretical argument. The theory explicitly posits that activists strategically respond to repression by leveraging the heightened visibility that follows such events. Rather than viewing media attention as an exogenous confounder, this study conceptualizes it as part of the opportunity structure that activists recognize and act upon.

However, interpreting what Twitter interactions, particularly decreased assortativity, actually indicate remains crucial. These shifts may reflect strategic outreach, performative solidarity, or general activity increases. While increased media attention may lead to more overall engagement, we would expect this to manifest as a broad rise in tweet volume or follower growth. In contrast, what we observe is a structural shift: targeted increases in cross-group retweeting without proportional increases in overall activity levels or network density. Twitter activities, especially between clusters, turn out to be not random. This makes them a plausible proxy for strategic coalition-building, rather than mere symbolic gestures or activity noise. While fully disentangling all mechanisms may be difficult, the timing and pattern of the observed shifts support the interpretation that activists are indeed making strategic use of moments of heightened visibility to broaden their alliances.

One more factor to consider is the timing of the events themselves, mass arrests and eviction threats occurred on different days of the week, which could influence online activity patterns due to variations between weekday and weekend usage. While these factors cannot be fully ruled out with the current design, the consistency of observed trends across two separate repressive events, combined with the relative stability of interaction patterns during the inter-repression period, lends support to the interpretation that the changes reflect strategic adaptations rather than random fluctuations.

While these alternative explanations are unlikely to serve as major confounding factors in this study, they nonetheless raise important questions that future research could explore more directly. Investigating how online and offline dynamics interact, how coordination emerges in decentralized movements, or how media cycles shape digital strategy would offer valuable insights into the broader mechanisms of protest behavior in networked environments.

Conclusion

This study provides both theoretical and methodological contributions. Theoretically, unlike much of the existing literature that frames repression primarily as a structural constraint or a source of cost for protest movements, this article conceptualizes repression as a potential opportunity for online activist groups to strategically promote themselves. Rather than assuming that online actors simply mirror offline protest dynamics, this article argues that online activism follows distinct mechanisms that are not necessarily dependent on offline developments. Online activist groups can strategically position themselves to support and promote offline protest groups with aligned interests, thereby functioning as an independent rather than a dependent variable in protest dynamics.

In doing so, this article introduces a strategic tension that online activists must navigate: expanding their support base without alienating their core followers. It argues that repression temporarily moves the strategic balance toward expansion, while more peaceful inter-repression periods require a shift back to retention to prevent defection and preserve group identity. By theorizing this strategic tension, the article is able to uncover a nuanced pattern in the interaction behaviors of online activists.

This study also moves beyond the conventional focus on state-protest dynamics to engage with the internal politics of protest movements. It demonstrates that protest groups are motivated not only by a desire to support the broader cause but also by efforts to advance their specific agendas and avoid marginalization. Online activists operate in much the same way, leveraging digital platforms to compete for visibility, assert their presence, and signal influence within the movement. While this decentralized and competitive process may ultimately contribute to greater movement cohesion, exploring that possibility may be for future research.

Methodologically, this study combines topic modeling, community detection, and network metrics to measure inter-group interaction dynamics among online activists. By applying ARIMA-based Interrupted Time Series modeling and permutation testing to relational indicators such as assortativity and cross-group ties, the study offers a novel strategy for identifying temporal shifts in protest behavior around moments of state repression. These approaches advance the methodological tools available for studying digital contention and protest network evolution over time.

While this study provides empirical insights into how activists adapt their online engagement strategies in response to offline repression, its scope presents several limitations that warrant discussion regarding generalizability. The analysis focuses exclusively on Twitter interactions among users based in New York City during the 2011 Occupy Wall Street movement. Although New York was the epicenter of the movement and a focal point of both mobilization and repression, this localized focus may not fully capture the broader dynamics of the Occupy movement, particularly in other cities or national contexts. Activists operating in different geographic settings, such as Oakland or London, may have experienced and responded to repression differently depending on local political environments, police behavior, and organizational networks.

Furthermore, this study examines only one digital platform, Twitter, which has specific structural and algorithmic features that shape how users interact. For example, Twitter's character limits, emphasis on real-time information, and public follower networks may facilitate fast, audience-oriented engagement in ways that do not easily translate to more private or visual platforms such as Facebook or Instagram. As such, the findings may not be directly generalizable to activism conducted on other platforms with different affordances and audience dynamics.

Beyond platform and location, future research should examine how these dynamics vary across movements with different organizational structures. The Occupy movement was notably decentralized, with minimal hierarchical coordination, which may have made shifts in online interaction patterns more emergent and diffuse. In contrast, movements with more centralized leadership might display clearer coordination around message discipline or response timing in the face of repression. While this study does not directly assess whether the observed strategic shifts were guided by influential actors or emerged organically, the decentralized nature of Occupy suggests that the changes were likely driven by dispersed collective behavior rather than centralized planning. Future research could explore how coordination dynamics, whether led by opinion leaders or arising from networked interactions, influence protest strategies in varying organizational contexts. Additionally, different forms of repression, ranging from physical violence and mass arrests to digital surveillance and platform censorship, may generate different strategic responses, depending on the perceived risks and costs of engagement. Finally, political context matters: patterns observed in a liberal democracy like the United States may not hold in more authoritarian environments, where the consequences of dissent can be far more severe.

Despite these limitations, the core theoretical logic developed in this study may extend beyond the specific setting of Occupy Wall Street in New York and the affordances of Twitter. The argument that repression can catalyze a strategic shift among online activists from internal consolidation to broader external visibility is rooted in a fundamental tension that any digitally networked movement is likely to face: how to grow public support without compromising group cohesion. This tension may not be platform-dependent or geographically confined. While the manifestation of such shifts may vary, taking different forms in authoritarian versus democratic regimes, or across hierarchical versus decentralized movements, the underlying strategic calculus might remain relevant. In this sense, the findings offer a transferable framework for understanding how repression can serve as a trigger for strategic reorientation in online activism, even if the specific expressions of that reorientation differ across contexts.

This study also carries practical implications for activists and policymakers. For activists, the findings suggest that repressive episodes can also serve as strategic windows of opportunity to broaden alliances, project solidarity, and amplify visibility beyond one's core group. However, the results also caution against prolonged outward engagement at the expense of internal cohesion, highlighting the importance of recalibrating strategies in response to shifting political conditions. For policymakers concerned with civil liberties and democratic resilience, the study underscores how repression can unintentionally stimulate digital mobilization by increasing public attention and incentivizing inter-group outreach. These dynamic raises important questions about the efficacy and unintended consequences of coercive tactics in managing dissent.

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Data Availability Statement

The data is available upon request.

Notes

1. This article focuses on a specific form of repression: observable, coercive actions involving the use of force by state agents such as police or the military. This definition draws on the typology developed by Earl (2003), who distinguishes repression along three dimensions: 1) the identity of the repressive agent, 2) the character of the repressive action, and 3) its observability. Focusing on observable state-led repression aligns with this study's theoretical emphasis on how activists strategically respond to public displays of coercion. First, although non-state actors may also engage in repressive acts, the state remains the primary and most capable agent of large-scale coercive interventions against protest. Second, observable repression plays a crucial signaling role: it generates visible, widely shared moments of crisis that activists can leverage to draw public attention, reframe narratives, and expand their support base. Unlike covert repression, which may suppress dissent silently, visible state violence creates moments of political salience that online activists can strategically capitalize on to shift engagement patterns and promote aligned protest groups.
2. In this study, online activists are defined as individuals who actively engage on digital platforms to support both the general goals of a protest movement and the specific agendas of constituent groups. This definition does not exclude individuals who also attend physical protests, as long as they maintain an active online presence.
3. As Benford and Snow (2000) note, efforts to extend frames often triggered internal conflicts within movements, particularly over ideological purity, strategic efficiency, and organizational boundaries.
4. This kind of strategic recalibration is not unique to the online sphere. Prior research has shown that coercive threats often prompt tactical adjustments in physical protest settings as well, such as shifts in organizing strategies, framing, or alliance-building (Almeida, 2008; Francisco, 1996). These findings suggest that repression reshapes dissent not only by suppressing participation but also by altering the organizational and strategic contours of collective action.
5. The Louvain algorithm is an efficient algorithm designed to optimize modularity by merging nodes into communities. Modularity is a measure that assesses the density of connections within communities in relation to the connections between communities. The algorithm terminates when no further merging of nodes leads to an increase in modularity (Smith et al., 2020).
6. Although it is difficult to determine the precise number of preferences within the Occupy Wall Street movement, the number of topics for the LDA model is adjusted to five to capture the diverse preferences and agendas encompassed within the movement. Details of the topics can be found in the Appendix.
7. The Cramer's V value between the Louvain community and topic assignments is approximately 0.32, while that between the Leiden community and topic assignments is around 0.34. These moderate association levels suggest a noticeable disconnect between online participants' topical interests and their organizational online groupings.
8. Topic modeling and community detection were performed separately for each protest phase, rather than using a global labeling across time. By doing so, this approach captures the evolving structure and composition of the protest network, as participants' affiliations and salient issues may change over time. Recomputing group assignments per phase allows the analysis to detect genuine structural transformations and the emergence of new topics, rather than forcing later developments into early-stage categories. Importantly, this design does not undermine tracing changes in assortativity over time. On the contrary, it

ensures that assortativity is measured against contemporaneous groupings, minimizing the risk of misinterpreting structural changes as artifacts of outdated classifications.

References

Almeida, P. (2008). *Waves of protest: Popular struggle in El Salvador, 1925-2005*. University of Minnesota Press.

Araj, B. (2008). Harsh state repression as a cause of suicide bombing: The case of the Palestinian–Israeli conflict. *Studies in Conflict & Terrorism*, *31*(4), 284–303. https://doi.org/10.1080/10576100801925273

Arslanalp, M., & Erkmen, T. D. (2025). Resistance under confinement: Resilience of protests and their limits in authoritarian Turkey. *Third World Quarterly*, *46*(2), 170–192. https://doi.org/10.1080/01436597.2024.2355163

Bakke, K. M., Cunningham, K. G., & Seymour, L. J. M. (2012). A plague of initials: Fragmentation, cohesion, and infighting in civil wars. *Perspectives on Politics*, *10*(2), 265–283. https://doi.org/10.1017/S1537592712000667

Beissinger, M. R. (2013). The semblance of democratic revolution: Coalitions in ukraine's Orange revolution. *American Political Science Review*, *107*(3), 574–592. https://doi.org/10.1017/S0003055413000294

Bell, S. R., & Murdie, A. (2018). The apparatus for violence: Repression, violent protest, and civil war in a cross-national framework. *Conflict Management and Peace Science*, *35*(4), 336–354. https://doi.org/10.1177/0738894215626848

Benford, R. D., & Snow, D. A. (2000). Framing processes and social movements: An overview and assessment. *Annual Review of Sociology*, *26*(1), 611–639. https://doi.org/10.1146/annurev.soc.26.1.611

Buccafurri, F., Lax, G., & Nocera, A. (2015). A new form of assortativity in online social networks. *International Journal of Human-Computer Studies*, *80*, 56–65. https://doi.org/10.1016/j.ijhcs.2015.03.006

Chang, P. Y. (2008). Unintended consequences of repression: Alliance formation in south korea's democracy movement (1970-1979). *Social Forces*, *87*(2), 651–677. https://doi.org/10.1353/sof.0.0153

Cunningham, K. G., Dahl, M., & Frugé, A. (2017). Strategies of resistance: Diversification and diffusion. *American Journal of Political Science*, *61*(3), 591–605. https://doi.org/10.1111/ajps.12304

Earl, J. (2003). Tanks, tear gas, and taxes: Toward a theory of movement repression. *Sociological Theory*, *21*(1), 44–68. https://doi.org/10.1111/1467-9558.00175

Earl, J. (2011). Political repression: Iron fists, velvet gloves, and diffuse control. *Annual Review of Sociology*, *37*(1), 261–284. https://doi.org/10.1146/annurev.soc.012809.102609

Earl, J., & Beyer, J. L. (2014). The dynamics of backlash online: Anonymous and the battle for WikiLeaks. In L. M. Woehrle (Ed.), *Research in social movements, conflicts and change* (*37*, pp. 207–233). Emerald Group Publishing Limited. https://doi.org/10.1108/S0163-786X20140000037007

Feldstein, S. (2021). *The rise of digital repression: How technology is reshaping power, politics, and resistance*. Oxford University Press.

Finkel, E. (2015). The phoenix effect of state repression: Jewish resistance during the holocaust. *American Political Science Review*, *109*(2), 339–353. https://doi.org/10.1017/S000305541500009X

Francisco, R. (2004). After the massacre: Mobilization in the wake of harsh repression. *Mobilization: An International Quarterly*, *9*(2), 107–126. https://doi.org/10.17813/maiq.9.2.559246137656n482

Francisco, R. A. (1995). The relationship between coercion and protest: An empirical evaluation in three coercive states. *Journal of Conflict Resolution*, *39*(2), 263–282. https://doi.org/10.1177/0022002795039002003

Francisco, R. A. (1996). Coercion and protest: An empirical test in two democratic states. *American Journal of Political Science*, *40*(4), 1179. https://doi.org/10.2307/2111747

Gohdes, A. R. (2015). Pulling the plug: Network disruptions and violence in civil conflict. *Journal of Peace Research*, *52*(3), 352–367. https://doi.org/10.1177/0022343314551398

Gohdes, A. R. (2020). Repression technology: Internet accessibility and state violence. *American Journal of Political Science*, *64*(3), 488–503. https://doi.org/10.1111/ajps.12509

González-Bailón, S., Borge-Holthoefer, J., & Moreno, Y. (2013). Broadcasters and hidden influentials in online protest diffusion. *American Behavioral Scientist*, *57*(7), 943–965. https://doi.org/10.1177/0002764213479371

Gurr, T. R. (1970). *Why men rebel (4. Printing)*. Princeton University Press.

Hafner-Burton, E. M., Kahler, M., & Montgomery, A. H. (2009). Network analysis for international relations. *International Organization*, *63*(3), 559–592. https://doi.org/10.1017/S0020818309090195

Honari, A. (2018a). From 'the Effect of Repression' Toward 'the response to repression. *Current Sociology. La Sociologie Contemporaine*, *66*(6), 950–973. https://doi.org/10.1177/0011392118787585

Honari, A. (2018b). "we will either find a way, or make one": How Iranian green movement online activists perceive and respond to repression. *Social Media + Society*, *4*(3), Article 2056305118803886. https://doi.org/10.1177/2056305118803886

Honari, A., & Muis, J. (2021). Refraining or resisting: Responses of green movement supporters to repression during the 2013 Iranian presidential elections. *Global Policy*, *12*(S5), 106–118. https://doi.org/10.1111/1758-5899.13000

Huang, H. (2018). The pathology of hard propaganda. *The Journal of Politics*, *80*(3), 1034–1038. https://doi.org/10.1086/696863

Kang, S. (2023). Upping the Ante Without Taking up Arms: Why Mass Movements Escalate Demands. *Journal of Peace Research*, *60*(1), 73–87. https://doi.org/10.1177/00223433221137614

Khawaja, M. (1993). Repression and popular collective action: Evidence from the west bank. *Sociological Forum*, *8*(1), 47–71. https://doi.org/10.1007/BF01112330

Kitschelt, H. P. (1986). Political opportunity structures and political protest: Anti-nuclear movements in four democracies. *British Journal of Political Science*, *16*(1), 57–85. https://doi.org/10.1017/S000712340000380X

Lichbach, M. I. (1987). Deterrence or escalation? The puzzle of aggregate studies of repression and dissent. *Journal of Conflict Resolution*, *31*(2), 266–297. https://doi.org/10.1177/0022002787031002003

Lichbach, M. I. (1994). What makes rational peasants revolutionary? Dilemma, paradox, and irony in peasant collective action. *World Politics*, *46*(3), 383–418. https://doi.org/10.2307/2950687

Lusan, N. N., Hlaing, K. H., & Fishbein, E. (2021). *Sarong revolution: Women smash gender taboos to fight Myanmar junta*. Vice. https://www.vice.com/en/article/bvxej5/sarong-revolution-women-smash-gender-taboos-to-fight-myanmar-junta

Malik, M., Lamba, H., Nakos, C., & Pfeffer, J. (2021). Population bias in geotagged tweets. *Proceedings of the International AAAI Conference on Web and Social Media*, *9*(4), 18–27. https://doi.org/10.1609/icwsm.v9i4.14688

McCarthy, J. D., & Zald, M. N. (1977). Resource mobilization and social movements: A partial theory. *American Journal of Sociology*, *82*(6), 1212–1241. https://doi.org/10.1086/226464

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, *27*(1), 415–444. https://doi.org/10.1146/annurev.soc.27.1.415

Meyer, D. S. (2004). Protest and political opportunities. *Annual Review of Sociology*, *30*(1), 125–145. https://doi.org/10.1146/annurev.soc.30.012703.110545

Moore, W. H. (1998). Repression and dissent: Substitution, context, and timing. *American Journal of Political Science*, *42*(3), 851. https://doi.org/10.2307/2991732

Morozov, E. (2011). *The net delusion: How not to liberate the world (1. Publ)*. Allen Lane.

Newman, M. E. J. (2002). Assortative mixing in networks. *Physical Review Letters*, *89*(20), Article 208701. https://doi.org/10.1103/PhysRevLett.89.208701

O'Brien, K. J., & Deng, Y. (2015). Repression backfires: Tactical radicalization and protest spectacle in rural China. *Journal of Contemporary China*, *24*(93), 457–470. https://doi.org/10.1080/10670564.2014.953849

O'Hearn, D. (2009). Repression and solidary cultures of resistance: Irish political prisoners on protest. *AJS; American Journal of Sociology*, *115*(2), 491–526. https://doi.org/10.1086/599249

Oliver, P. (1980). Rewards and punishments as selective incentives for collective action: Theoretical investigations. *American Journal of Sociology*, *85*(6), 1356–1375. https://doi.org/10.1086/227168

Olson, M. (1971). *The logic of collective action: Public goods and the theory of groups*. Harvard University Press.

Osa, M. (2003). *Solidarity and contention: Networks of Polish opposition*. University of Minnesota Press.

Papadopoulos, S., Kompatsiaris, Y., Vakali, A., & Spyridonos, P. (2012). Community detection in social media: Performance and application considerations. *Data Mining and Knowledge Discovery*, *24*(3), 515–554. https://doi.org/10.1007/s10618-011-0224-z

Parkinson, S. E. (2013). Organizing rebellion: Rethinking high-risk mobilization and social networks in war. *American Political Science Review*, *107*(3), 418–432. https://doi.org/10.1017/S0003055413000208

Pearlman, W. (2013). Emotions and the microfoundations of the Arab uprisings. *Perspectives on Politics*, *11*(2), 387–409. https://doi.org/10.1017/S1537592713001072

Penney, J., & Dadas, C. (2014). (re)tweeting in the service of protest: Digital composition and circulation in the occupy wall street movement. *New Media & Society*, *16*(1), 74–90. https://doi.org/10.1177/1461444813479593

Prochnow, T., Patterson, M. S., Bridges Hamilton, C. N., & Umstattd Meyer, M. R. (2022). Summer friends and physical activity: Social network effects on child self-reported physical activity at summer care programs. *Health Education & Behavior*, *49*(5), 770–779. https://doi.org/10.1177/10901981221076399

Reynolds-Stenson, H. (2022). *Cultures of resistance: Collective action and rationality in the anti-terror age*. Rutgers University Press.

Rød, E. G., & Weidmann, N. B. (2015). Empowering activists or autocrats? The internet in authoritarian regimes. *Journal of Peace Research*, *52*(3), 338–351. https://doi.org/10.1177/0022343314555782

Ryckman, K. C. (2020). A turn to violence: The escalation of nonviolent movements. *Journal of Conflict Resolution*, *64*(2–3), 318–343. https://doi.org/10.1177/0022002719861707

Saab, R., Tausch, N., Spears, R., & Cheung, W.-Y. (2015). Acting in solidarity: Testing an extended dual pathway model of collective action by bystander group members. *The British Journal of Social Psychology*, *54*(3), 539–560. https://doi.org/10.1111/bjso.12095

Savio, G. (2015). Coordination outside formal organization: Consensus-based decision-making and occupation in the occupy wall street movement. *Contemporary Justice Review*, *18*(1), 42–54. https://doi.org/10.1080/10282580.2015.1005509

Siegel, D. A. (2011). When does repression work? Collective action in social networks. *The Journal of Politics*, *73*(4), 993–1010. https://doi.org/10.1017/S0022381611000727

Smith, L. G. E., Gavin, J., & Sharp, E. (2015). Social identity formation during the emergence of the occupy movement: Social identity formation during occupy wall street. *European Journal of Social Psychology*, *45*(7), 818–832. https://doi.org/10.1002/ejsp.2150

Smith, N. R., Zivich, P. N., Frerichs, L. M., Moody, J., & Aiello, A. E. (2020). A guide for choosing community detection algorithms in social network studies: The question alignment approach. *American Journal of Preventive Medicine*, *59*(4), 597–605. https://doi.org/10.1016/j.amepre.2020.04.015

Sullivan, C. M., & Davenport, C. (2017). The rebel alliance strikes back: Understanding the politics of backlash mobilization. *Mobilization: An International Quarterly*, *22*(1), 39–56. https://doi.org/10.17813/1086-671X-22-1-39

Tilly, C. (1978). *From mobilization to revolution* (1st). McGraw-Hill Publ.

Titarenko, L., McCarthy, J., McPhail, C., & Augustyn, B. (2001). The interaction of state repression, protest form and protest sponsor strength during the transition from communism in minsk, Belarus, 1990-1995. *Mobilization: An International Quarterly*, *6*(2), 129–150. https://doi.org/10.17813/maiq.6.2.t1461545p3470856

Traag, V. A., Waltman, L., & Van Eck, N. J. (2019). From louvain to leiden: Guaranteeing well-connected communities. *Scientific Reports*, *9*(1), 5233. https://doi.org/10.1038/s41598-019-41695-z

Ward, M. D., Stovel, K., & Sacks, A. (2011). Network analysis and political science. *Annual Review of Political Science*, *14*(1), 245–264. https://doi.org/10.1146/annurev.polisci.12.040907.115949

White, R. W. (1989). From peaceful protest to guerrilla war: Micromobilization of the provisional Irish republican army. *American Journal of Sociology*, *94*(6), 1277–1302. https://doi.org/10.1086/229155

Wood, E. J. (2015). The emotional benefits of insurgency in El Salvador. In J. Goodwin & J. M. Jasper (Eds.), *The social movements reader: Cases and concepts* (pp. 143–152). Blackwell Publishing Ltd.

Wozniak, K., Drakulich, K., & Calfano, B. (2020). Theories of public opinion change versus stability and their implications for null findings. *CrimRxiv*. https://doi.org/10.21428/cb6ab371.bb19339e

Xu, X. (2021). To repress or to co-opt? Authoritarian control in the age of digital surveillance. *American Journal of Political Science*, *65*(2), 309–325. https://doi.org/10.1111/ajps.12514

Yangfang, T. (2012). A review of the 'Occupy Wall Street' movement and its global influence. *International Critical Thought*, *2*(2), 247–254. https://doi.org/10.1080/21598282.2012.684287

Zech, S. T., & Gabbay, M. (2016). Social network analysis in the study of terrorism and insurgency: From organization to politics. *International Studies Review*, *18*(2), 214–243. https://doi.org/10.1093/isr/viv011

Zhukov, Y. M. (2023). Repression works (just not in moderation). *Comparative Political Studies*, *56*(11), 1663–1694. https://doi.org/10.1177/00104140231152778

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Appendix

Table 1A. Network Metrics by Phase

Metric	Phase 1	Phase 2	Phase 3
Nodes	1,835	1,835	1,835
Edges	676	1,105	1,340
Density	0.000	0.001	0.001
Mean degree	0.737	1.204	1.460
Degree 25th	0	0	0
Degree median	0	0	0
Degree 75th	1	1	1
Giant component ratio	0.245	0.338	0.380
Avg clustering	0.082	0.114	0.143

Table 2A. Top Words for Topics

Phase	Topic	Top words
Phase 1	1	protest http, arrested protest, facebook page, page car, car pool
Phase 1	2	check video, pepper spray, michael moore, protest http, protesters http
Phase 1	3	pm http, radiohead pm, confirmed radiohead, protest http, tahrir square
Phase 1	4	video http, protests http, police brutality, email messages, yahoo blocking
Phase 1	5	day http, protests http, cont http, michael moore, pepper spray
Phase 2	1	brooklyn bridge, movement http, gt gt, gt http, video http
Phase 2	2	kanye west, fox news, protest http, protesters http, russell simmons
Phase 2	3	http fxtzreo, video http, song wrote, vid http, original song
Phase 2	4	cont http, veterans peace, brooklyn bridge, movement http, fox news
Phase 2	5	protesters http, check video, brooklyn bridge, video http, march http
Phase 3	1	movement http, message won, won http, read http, fighting read
Phase 3	2	Times square, zuccotti park, vote http, square http, rich anthem
Phase 3	3	protesters http, news http, movement http, fox news, protest http
Phase 3	4	movement http, video http, times square, protesters http, zuccotti park
Phase 3	5	video http, protesters http, movement http, check video, times square

Table 3A. Community Statistics

Phase	Community type	Total communities	Max size	Min size	Mean size
Phase 1	Community (Louvain)	498	3,373	1	19.77
Phase 2	Community (Louvain)	1,602	18,341	1	28.73
Phase 3	Community (Louvain)	2,833	34,461	1	29.01
Phase 1	Community (Leiden)	492	3,200	1	20.01
Phase 2	Community (Leiden)	1,604	17,434	1	28.70
Phase 3	Community (Leiden)	2,844	32,925	1	28.90