State Embeddedness and Field Stability: The Tea Party and Occupy Wall Street's Interorganizational Networks

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Abstract. Despite widespread scholarly attention on social movement media coverage, the full range of organizations appearing in the media with movements remains underexamined. To analyze this organizational complexity, we draw upon field theory, relating it to concepts from social network analysis. We hypothesize that interactions with state-embedded actors increase field stability, yet this effect decreases with the field's level of abstraction. We contrast a pair of US movements, the Tea Party and Occupy Wall Street, according to their interactions with state-embedded actors. Through the New York Times's API, we collect and produce article co-appearance networks that approximate the population of Times's indexed organizations. We parse fields from these networks using community detection algorithms. Our analyses test stability using triadic closure propensities and average coreness. Our findings show that subgroups affiliated with the Tea Party had greater stability than those of Occupy Wall Street.

Keywords: Social networks · News media · Social movements · Organizations

1 Introduction

Social movements research using data from news media sources has recently blossomed. This research has expanded upon diverse topics that include movement media coverage, tactics, policy and market outcomes, and targets [e.g., 3, 28, 53]. Within this large research body, two subjects remain relatively unexamined: the ubiquitous presence of non-movement organizations and their social networks, which may or may not include movement actors.

Scholarship has increasingly emphasized interactions between social movements and non-state organizations. Calls for such emphases span decades [11, 48] and have been reinvigorated by integrating social movements within field theory and multi-institutional politics [4, 14, 19, 20, 47]. Empirical progress demonstrating the interaction between movement and non-movement organizations has made great strides in analyzing relationships between movements and market actors [29] among other non-movement organizations [16]. Works demonstrating such interaction, typically focus upon non-movement actors as entities vulnerable to movement action (e.g., targets), supporters or adversaries, or instruments that voice movement interests. While these studies move beyond the “movement-centric” criticisms of movement theory [19, 20], their research designs largely place relational emphases on a “two-party struggle” [48:197], ignoring a vast number of organizations within the broader field of action.

Social network theory and analysis provides one way to capture such organizational complexity [34]. Scholarship on interorganizational network has unquestionably advanced social movements research [e.g., 13, 14, 32, 53]. Of these studies, two works that used newspaper data to construct social networks [5, 53] restricted their analyses to movement organizations and protest events. Other remaining works analyze interorganizational networks that are small-to-moderate sized in terms of the number of organizations and, exempting one study [41], focus on university or city-specific research universes, rendering generalizations to newspaper coverage on a larger scale difficult.

We collect and analyze two networks constructed from newspaper data that approximate all organizations recognized by the New York Times (NYT) during the analyzed time periods. Each network spans a coverage period associated with two movements: the Tea Party (TP) and Occupy Wall Street (OWS). To introduce our guiding theoretical framework, we briefly review the literature on fields. Given implications in the literature, we suggest that interactions with state-embedded actors stabilizes fields. Due to TP's formal inclusion into US national politics and OWS's ultimate repression, we suspect that fields associated with TP will offer greater stability. Following new institutionalist studies, we identify fields based upon dense network ties and use structural cohesion to characterize the stability within the fields [44]. We analyze field stability alongside "movement-centric" subgroups generated from network neighborhoods. We conclude our study by encouraging future social movement studies to engage in multi-institutional research and expand upon similar network datasets.

2 Organizations, Fields, and Social Movements

Scholarship on organizations have benefited greatly due to the popularization of the organizational fields concept, defined as the "sets of organizations that, in the aggregate, constitute a recognized area of institutional life" [15:148-9]. Here, we understand institutions as sets of rules that develop through social interactions [18:106].

The concepts of fields and institutions have proven resonant among social movement scholars [47, 4, 14, 19, 20]. Synthesizing two disparate approaches, one study characterizes a field as having regular (inter)action within itself, agreement among participants regarding the "rules of the game," and potential vulnerability to field external forces [47:124]. An additional study encouraged analysts to consider the many non-state institutions with whom movements interact [4], a point strongly emphasized by a later study which conceptualized fields "as sets of actors characterized by high relational density and actors' reciprocal recognition" [14:265]. Recent work on "strategic action fields," defined as "a meso-level social order where actors...interact with knowledge of one another under a set of common understandings about the purposes of the field, the relationships in the field..., and the field's rules" [19:3], has operationalize field membership as "those groups who *routinely* take each other into account in their actions" [20:167-8]. Though differing in some ways, the literature converges upon characterizing a field based on frequent interactions between recognizable actors who more-or-less understand the field's "rules."

In addition to this characterization, scholars have describe fields and organizational networks as a nested phenomenon [4:82, 19, 20]. "Strategic action fields," for instance, are generally couched within other strategic action fields, like the nested layers of Russian matryoshka dolls [19, 20]. Though vocabulary differs between studies, the central premises hold that smaller fields are embedded within larger fields and that smaller fields are more specialized, yielding more similarities among their member organizations than their larger, enveloping fields. This process of field aggregation will therefore accompany heterogeneity in both its interaction patterns and understood rules.

Though movements may engage within any of a vast array of fields, analysts must consider structural variation between fields. Recent scholarship has presented three basic field phases: emergence, crisis, and stability [19, 20]. Of these three phases, we are most interested in contrasting emergent and stable fields. Actors in emergent fields possess limited agreement regarding field rules, maintain tenuous alliances with actors from other fields, are unsure regarding challenger outcomes, and are vulnerability to state action. On the flipside, stable fields follow well-established, known rules of an "ongoing game" in which incumbents, challengers, and their political coalitions jockey for improved positions through iterative moves and countermoves. A field's stability hypothetically arises from many ties to other fields, invulnerability to turbulences in its resource dependencies, and its relationship to the state, an institution with the capability to reshape field rules [19, 20].

Fields comprised of organizations with frequent ties or long-standing relationships to actors embedded in state affairs likely enjoy greater stability than those without. We reach this hypothesis from three main points. First, we should consider that state-embedded actors may or may not even interact with challengers--even if the challenger orients its action to the state. In the case of the United States, such interactions typically coincide with national elections, times when challengers compete to influence political party platforms [2:292]. Second, given the descriptions of field phases [19, 20], we suggest that high-capacity nation states generally constitute stable fields, as they meet the characteristics of emergent fields only following revolutions. Third, among professions, one study [15] points to the role of the state in driving organizational isomorphism--the process by which organizations and their fields become similar in form. Two of this study's field-level hypotheses posit that a field's resource dependence and transaction with state agents yield higher levels of isomorphism across all organizations within the field. To the extent that state-embedded actors like the Republican and Democratic parties include challengers, we expect that challenger inclusion corresponds with frequent ties and a high degree of isomorphism for both challengers and incumbents. If we characterize state fields as stable, fields that depend upon and frequently engage with the state should therefore adopt stable forms more than other fields. Lastly, following fields' nested characterizations, as a field expands to include relatively fewer interactions with and dependence upon state-embedded actors, its stability should diminish.

3 Case Overviews

For this paper, we contrast two cases, the Tea Party and Occupy Wall Street. We focus on these two movements due to their large size, national media coverage, and historical proximity. Though other studies have compared these two movements, such as their approaches to populism [54] among others, ours highlights their relationships to other movement and non-movement organizations.

3.1 Tea Party

The Tea Party was initially hailed as a spontaneous grassroots movement that emerged in early 2009 to oppose a variety of issues including the election of Barack Obama, proposed health care reform, and increased taxation in early 2009 [55]. As TP grew in popularity it expanded the initial focus on resisting increased government services, encompassing a wide array of traditionally conservative causes including taxation, smaller government, along with wider economic and social issues such as immigration, welfare, and affirmative action.

The nature of TP protests is contentious, with their members making claims of being a wholly grass-roots movement [40] and opponents claiming that the movement is mostly 'astroturf,' a fake grassroots movement completely backed and orchestrated by monied interests [55]. The narrative advanced by TP organizations and most affiliated groups is that the movement is "100% grassroots, 100% of the time" [50] a stance that allows the movement to frame itself as a scrappy outsider unconnected to current institutional insiders.

Those arguing that the Tea Party grew out of, and enjoyed the support of, existing political organizations and movements point to the significant resources from established political interests including the Republican Party and think tanks like Americans For Prosperity and FreedomWorks, all of which had activists and resources invested in the movement [55]. This support is credited as helping to elect members of the "Tea Party Caucus" in both the House and Senate in the 2010 elections. Additionally, TP groups often are financially supported by industry and conservative think tanks like Americans for Prosperity and the Heartland Institute. But TP groups are often at odds with mainstream Republican policies and are more likely to support libertarian ideals and causes when these causes are in conflict with a broader conservative agenda.

This second account seems more supported by the gradual movement of the Tea Party towards alliances with institutionally powerful organizations and political parties. Despite their claims of local grassroots control, TP was able to quickly mobilize or recruit several members who successfully ran for public office at both the state and federal level in 2010 with an even greater number running and failing to win public office. This would seem to indicate that TP was able to make linkages with institutionally powerful organizations within its field, and not just constraint itself to decentralized local chapters with few ties at the national level.

Our data on TP's media presence covers the period from February 27, 2009 which was the date of the first national TP protests, to November 2, 2010 the date of the first general elections in which the movement played a significant role.

3.2 Occupy Wall Street

Occupy Wall Street represents the most recent incarnation of the long lived tradition of movements focused on social justice and the alleviation of income and other inequalities. Initially formed in September of 2011 under the auspices of the Canadian anti-consumerist group Adbusters, the OWS movement held its first major protest event on September 17, 2011 in New York City's Zuccotti Park. However, its roots trace inspiration from the Spanish economic protests of the prior May, which in turn were inspired by the events of the pro-democracy Arab Spring [26].

During this period of time OWS spread to a plethora of other cities and gained considerable attention of the national news media. The period witnessed the emergence of other social movement groups who addressed issues pertinent to OWS's interests, including hacktivist groups like Anonymous [8], as well as other social justice and traditional left-wing groups. During the early days of the movement these diverse interests vied to set the agenda of the overall movement and attempted to link the overall movement goal of inequality with a myriad of local and national issues [46]. Occupy Wall Street was also quick to rebuff overtures from national political figures during this time, instead choosing to allow local occupation groups to retain a high degree of autonomy [21].

Our data encompass the first organized protest on September 17, 2011 until March 17, 2012. This end date marks the day six months after the start of the movement and corresponds with Occupiers' attempt to re-occupy Zuccotti Park, in which the group faced mass arrests and violence from police. This attempted re-occupation followed a period of general movement decline after police vigilantly cleared Occupy encampments across the country.

4 Methods of Analysis

4.1 Data

To take census of the fields present in the media, our study relies upon a network unique dataset collected from the New York Times Article Search API online [38].[1] The NYT Article Search API enables researchers and developers the ability to search all articles published by the New York Times between 1981 and the present. Beyond conventional search capabilities to identify articles by keyword strings contained in the text, the NYT Article Search API [38] also enables "facet" searches. Here, a facet refers to a type of tag used to index New York Times articles. The API's facets provide information on a descriptive subject (*des_facet*), relevant geographical information (*geo_facet*), the standardized names of organizations mentioned in the article (*org_facet*), notable persons mentioned (*per_facet*), among many other characteristics relevant to the article's classification. We focus almost exclusively upon the organizations tagged in each article using R version 2.14.1 script [45] with the packages RCurl [31] and rjson [9].

Generally, the New York Times indexers standardized facet names. To identify a concept's standardized name and relevant facets within the Times one must use the TimesTags API [39].We searched the TimesTags API for the terms "tea party" and "occupy" to find articles mentioning the TP and Occupy Wall Street. The API respectively returned "Tea Party Movement (Des)" and "Occupy Wall Street (Org)," indicating that we should only search for "Tea Party Movement" under the descriptive subject facet and "Occupy Wall Street" under the organizational facet. We retrieved all articles on TP between February 27, 2009 and November 2, 2010 and all articles on OWS between September 17, 2011 and March 17, 2012. The New York Times identified TP in 207 articles and tagged OWS in 294, after removing duplicates. Despite early movement coverage, the newspaper only began tagging TP on January 21, 2010. Taking TP's late tag implementation into consideration, it's little surprise that OWS received more coverage due to its point of origin and focus relative to the Times.

After we collected the articles tagging the Tea Party or Occupy Wall Street, we searched for a near population of articles with organizational tags through a crawling technique. The technique followed a five step process. First, we identified additional organizations from the organizational facets of the initial articles on TP and OWS. We did so separately, creating two lists: one of organizations tagged in TP articles and one of organizations tagged in OWS articles. We refer to these organizations as the sample's "first wave." Second, we search for all articles tagging these additional organizations. If we found additional organizations from the TP articles, we restricted the results to articles running between February 27, 2009 and November 2, 2010; for organizations discovered from OWS articles, we only searched for additional articles between September 17, 2011 and March 17, 2012. Third, we delete duplicate articles identified by the previous searches. Fourth, we identified additional organizations uncovered from the organizational facets of the first wave. These organizations constitute the sample's second wave. Fifth, we repeated the second through fourth steps until the fourth step could no longer identify any additional organizations. The process took eight waves for TP and seven waves for OWS. While this procedure cannot capture every organization ever tagged in the New York Times during these periods, it does capture all organizations tagged in the giant component of the New York Times's organizational network. Of great value to social movement research, the method generates a grounded, systematic list of organizations with potentially distant relations to the movements of interest.

[1] We abide by the terms of use put forth by the Article Search API [38]. In doing so we must acknowledge that the New York Times neither promotes nor endorses our research.

While the technique to use “facets” through a newspaper’s API is new to social movements research, it offers a technological update to established methods in the movements literature which used article indexing [e.g., 33:236-50, 33:267]. This method faces limitations which include practices of inclusiveness, thoroughness, and consistency exercised by newspaper indexers [17:68]. Rather than focusing upon protest coverage, the subject of criticism [17:68], our study addresses general patterns of organizational affiliations through mutual media coverage.

Following the data collection stage, we processed the data into two social networks. This stage included refining the list of organizations provided by the New York Times and converting organizational co-mentions within an article to edges (i.e., “ties” or “relationships”) in a social network. We split the data into two social networks: one created during the the Tea Party Movement’s time span and the other collected during Occupy Wall Street’s window. The Article Search API [38] produced a total of 4,852 organizations from the TP crawl and 2,923 organizations from the OWS crawl. Together, 6,330 organizations appeared in either crawl, leaving 1,445 organizations appearing in both. However, these counts include duplicate entries which the authors consolidated. Some “organizations” failed to meet our very general criteria for inclusion, though. These criteria include one or more living member dedicated to the maintenance of the organization and its purposeful activities, as well as a modest degree of independence or distinction in terms of personnel, purpose, or clientele from other organizations. Further, an organization must have the potential to exert agency. This criteria includes both subsidiaries and parent organizations. It removes products, projects, services, and websites, should their existence depend exclusively upon representing another organization. We err on the side of overinclusion, as closely related organizations should exist within the same field. We are then left with 4,504 organizations in the TP data and 2,825 in the OWS data, for a total of 5,812 unique organizations.

After determining organizational inclusion, we then created our networks, such that vertices represent organizations and edges portray each article that includes facets referencing two or more organizations. Our data includes the possibility for multiple edges between a pair of nodes, as two organizations are often co-tagged in more than one article. We do exclude “loops,” or relationships a node has with itself. We stored our network data and conducted all network analyses in this paper using igraph (version 0.6) for R [10].

4.2 Community Detection

Community detection identifies groups within a network that contain many ties among the group’s members and few ties between groups [36]. Scholars refer to this property of dense interaction within communities and sparse ties between as “modularity” [35]. Though the techniques differ, similar motivations emphasizing dense ties within groups have motivated other social movements analyses on group identification [5, 13, 14] and the study of fields [44]. As with field scholars, community detection values dense interactions among actors within groups. While community detection does not assuredly produce fields in which actors understand “the rules of the game,” the underlying premise behind this research is that “tight-knit” communities include members united by common attributes or themes [12]. Considering the definition of institutions [18:106], mutual rule understandings should emerge from groups marked by frequent interactions. This approach follows research that explicitly eschews a priori assumptions regarding institutional power, connections, and logics along with field boundary definitions ascribed by actor attributes [4:82 and 14]. For this article, we refer to the communities identified as “fields.”

Though field theorists add analytic complexity by conceptualizing their subject as a nested phenomenon, community detection researchers have developed techniques for this very problem [6]. “The Louvain method” detects communities by optimizing modularity in a hierarchical manner, looping through levels of aggregation. In the first pass, the method identifies many small, dense communities. Following this pass, the method then treats these communities as aggregated nodes within the network and identifies communities among these communities, or “meta-communities” [6:5]. The method repeats, treating these meta-communities as aggregated nodes, and so on, reducing the number of communities until the algorithm reaches optimal modularity. Each pass represents a distinct level of communities within communities differing from random association. The first level includes the most specific communities that feature the highest degree of association and this degree of association wanes as the levels increase.

4.3 Subgroups

We focus upon two subgroup types. Communities detected by the Louvain method serve as the first type. We apply this method to both TP and OWS datasets, allowing the method to interpret multiple edges (i.e., organizations co-faceted in multiple articles). Due to the method's focus on dense interaction patterns and nestedness, we liken Louvain communities to fields and use the terms synonymously throughout our analyses. We analyze the communities at each relevant level of the algorithm's aggregation, whereby higher levels indicate greater abstraction and relatively less interaction within groups than lower levels.

"Neighborhoods" serve as the second subgroup type. Neighborhood subgroups contain all actors tied to one focal actor along with all ties between them. Neighborhoods vary in "order" so as to include indirect ties to the focal actor. A first order neighborhood includes only those organizations with direct ties to TP or OWS. A second order neighborhood includes all organizations who belong to order one, as well as all other organizations with whom they share direct ties. Lastly, a third order neighborhood includes all organizations with direct ties to those in a second order neighborhood. We analyze the first through third order neighborhoods. Like levels within Louvain communities, as the order of a neighborhood increases, so too does the abstraction from its points of origin. Because we use two movements as the focal actors in these networks, we refer to these analyses as "movement-centric."

We operationalize subgroups this way for two reasons. First, we find value in comparing "movement-centric" and "field-centric" analyses. Louvain communities and neighborhoods offer a different perspectives to analyze distance from a movement's core. Louvain communities express this distance in levels marked by a decrease in tie density between actors. Neighborhoods express this distance in terms of path length from a focal actor. As the path length between actors increases, similarities should diminish. Second, these comparisons also offer verification against idiosyncratic properties of either method.

4.4 Stability

Among the concepts in social network analysis used to assess stability, cohesion ranks top. In principle, cohesion enables a subgroup to readily resist "disruptive forces" [25], generate social homogeneity [22], and enforce norms through social pressure [23:418-9]. While cohesion definitions vary [23:410], practically all analysts agree that *cliques* constitute a cohesive subgroup. A clique refers to a subgroup of size three or greater in which every member has a direct tie to every other member [51:254]. Triangles constitute the smallest clique and their closure has received considerable attention in numerous classic works [24; 27]. Analyzing closed triads, rather than dyads, offers at least three advantages relevant for this study [30:185]. First, the concept of a majority exists in groups of three or more, suppressing individual interests in favor of group interests. Second, no single member in closed triangles wields the power to dissolve the group should his or her demands go unmet. Third, groups of three address and resolve conflicts more readily than dyads due to third-party moderating effects. For these reasons, we use the proportion of triangles, the global clustering coefficient [43:2], on our simplified networks to measure of group stability. We apply this measure to each community.

Though most network analysts agree that cliques constitute a cohesive subgroup, most also consider the definition too "stingy" [23, 51] as it excludes near-cliques and most large groups. The concept of *k-cores* emerged as one popular responses to clique-based limitations by identifying dense, cohesive seedbeds within a network. k-cores measure cohesion by counting the minimum number of ties, k, each member of a subgroup has to other members within the subgroup [49, 51:266-7]. Likewise, "coreness" refers to a nodal property represented by c, where c captures if the node belongs to a c-core, but not a (c+1)-core [1]. Coreness represents the highest k-core a node belongs, where "highest" is accounted for by k. Higher values of k and coreness indicate greater cohesion. We simplify our networks, allowing up to just one tie between actors, and contrast TP and OWS's subgroups according to their average coreness scores. High average values of coreness indicate stability within the subgroup.

5 Analysis

5.1 Field Descriptions

We begin our analyses with an overview of the Louvain communities ("fields") associated with TP and OWS. In Table 1 we describe the subgroups associated with the two movements at each level. We provide counts for the number of organizations associated with each cohesive subgroup, the proportion of observed ties (i.e., density) within each subgroup, and name the five organizations added to the subgroup who received the most news coverage. Due to the number of organizations included in each field, we mention only a few widely covered ones in the table and name others in the text.

Table 1. Field Overview

Case	Level	n	Density	Examples
TP	1	107	0.045	Democratic Party, Republican Party, Tea Party, City Council, Park51
TP	2	385	0.013	Senate, House of Representatives, Supreme Court, EPA, Harvard
TP	3	390	0.013	NSF, NIST, American Assoc of University Women, Kennedy School of Government
TP	4	390	0.013	
OWS	1	60	0.046	Occupy Wall Street, Police Dept, NYT, FBI, City Council
OWS	2	145	0.020	Lincoln Center for the Performing Arts, Fire Depart, Anonymous, Juilliard School, Academy of Motion Picture Arts and Sciences
OWS	3	204	0.014	Education Depart, Olympus Corp, Parks and Rec Dept, Race to the Top Fund, Board of Regents

Like the concept of fields, the number of organizations within a Louvain community grows as the level of abstraction increases. Level 1 refers to the most specific group whose commonalities should be strongest according to the Louvain method's algorithm. Level 2 includes all organizations from Level 1, along with other related organizations whose Level 1 group differed from our movements of interest. Likewise Level 3 includes all organizations from Level 2 and also organizations from Level 2 groups that TP and OWS did not belong to. For OWS data, the Louvain method reached optimal modularity at Level 3, so a Level 4 does not exist in its network. The technique did suggest a Level 4 pass for TP's network data, yet this pass merged only two groups and did not affect the Louvain communities associated with the Tea Party: TP's Level 4 community contains the same organizations as its Level 3 community. For this reason, we exclusively discuss Levels 1 through 3.

The Tea Party belongs to state-embedded fields at each field level. As much of its faceted coverage pertained to the 2010 primaries and general election, naturally its Level 1 subgroup heavily represents political parties. In addition to the Republican and Democratic parties, this field also includes minor political parties and related organizations, such as the Democratic and Republican national committees. Notably, this field also includes some of the largest and most widely-covered US social movement organizations [3], such as the NAACP, the AARP, and the Sierra Club. It also involves large labor organizations, health and medical groups, and conservative think tanks. Broadly described, this field encompasses parties and movements successfully included in the political process. This field of national political contenders lies within two other larger fields with less well-defined boundaries. The level of abstraction from Level 1 to Level 2 marks a growth in over three and a half times as many organizations. In comparison, we observe a difference from TP's Level 2 to Level 3 field: the Level 2 field merges with just five organizations. Given the dramatic growth from Level 1 to Level 2, the diversity observed with TP's Level 2 field exceeds our ability to characterize its organizations. We would like to point out a few organizations whose affiliations with TP's most specific community, at Level 1, prove natural. One example of these include governmental organizations, such as two of the three branches of the federal government, federal agencies, and cabinet departments. These are, after all, the organizations that political parties seek to attain and politically-oriented national movements desire to influence. While many movement organizations do exist within TP's Level 2 community, their presence in this field is accompanied by lobbyists, elite private universities, energy firms, pharmaceutical companies, non-profit organizations, and other organizational types, many vying for political influence. Although these organizations frequently do influence the polity, their position exists one step beyond national political parties and electoral politics.

In contrast to the Tea Party, OWS's fields have relatively little to do with nationally-oriented politics. Their most specific community, Level 1, includes economic authorities, organizations related to parks and their occupation, churches, news agencies, California universities, online communities, and law enforcement agencies. The field did include some movement organizations along with apolitical and economic targets, support organizations and venues, news media groups, and authorities. Though some national-level organizations do exist within this field, by and large the field operates within a much smaller locus of conflict. As with TP, OWS's field diversity increases dramatically between the first and second levels. Its second level includes 30 fields identified from the first pass and many of them quite small, precluding the level from systematic characterization. In addition to OWS's Level 1 field, its Level 2 field included seven other Level 1 fields whose sizes exceed three organizations. These groupings included a number of organizations formed around arts and entertainment. The field also encompassed organizations involved in hacktivist conflict, associations for firefighters, those related to New York City prisons and hospitals, among others. As with Level 1, this field includes many organizations local in scope and excludes matters of national politics. The third level of OWS's field folds in an additional 59 organizations involved in five distinct Level 2 fields. These organizations address subjects of education, families and homelessness, local parks and circuses, the Olympus Scandal, and rock 'n roll. While the inclusion of these organizations increases the abstraction of OWS's field, in many ways they also extend the field's earlier interests in local institutions, community services, along with arts and entertainment.

Although these fields may seem quite broad, they *exclude* a great many organizations. Within TP dataset, the Louvain method also identified Level 4 fields associated with banking and finance; international affairs; retail, technology, and telecommunication; basketball; automobiles; and news among others. Within OWS, other Level 3 fields included organizations in banking and finance, universities and collegiate sports, high art, broadcasting corporations, international affairs, automobiles, soccer, and, of course, national parties and politics.

5.2 Neighborhood Description

While the Tea Party and Occupy Wall Street have an elevated propensity to appear in articles alongside other organizations within their same fields, they often co-appear in articles with other organizations. Figure 1 illustrates their first order neighbors in the simplified co-facet network. For visual clarity, we remove TP and OWS as they have direct ties to all organizations in their respective plots.

These movement-centric plots illustrate pronounced differences between the two movements. First, of the 33 organizations that appear in articles alongside TP, just four organizations have ties only to TP. The majority of TP's neighbors co-appear in articles with other organizations tied to TP. In contrast, of the 68 organizations mentioned in articles with Occupy Wall Street, 26 of these organizations never co-appear with any of the others,[2] suggesting that organizations within TP's neighborhood overlap in interests more frequently than those in OWS's neighborhood.

[2] An analysis of these numbers with a chi-squared test indicates a significant difference (X^2=6.060, $p<0.05$).

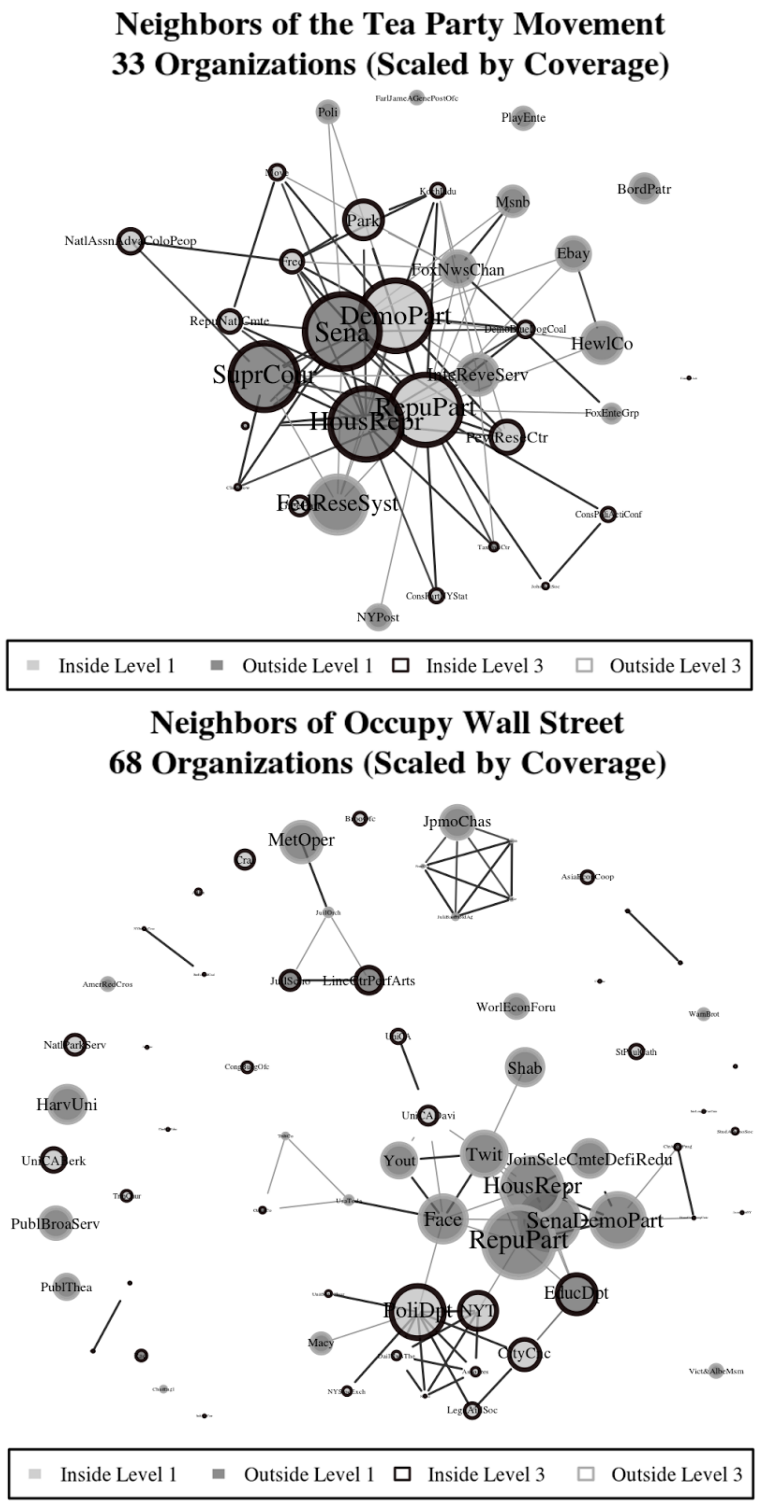

Fig. 1. Movement Neighborhoods

Second, even though the Louvain method parses OWS from national politics, the movement does co-appear in articles with some of these players, however their roles within neighborhood differ greatly from those of TP. Organizations such as the Democratic Party, the Republican Party, the House of Representatives, and the Senate appear quite central in TP's neighborhood. Within OWS's neighborhood, the role of these state actors is diminished. Further, they form a distinct cluster, featuring few ties to New York-based organizations, none to New York City arts organizations, yet they do have relatively more ties to social media outlets.

5.4 Comparing Subgroup Stability

For the following analyses, we test the hypothesis that due to its state-embedded affiliations, TP's fields and neighborhoods should demonstrate greater stability than those of OWS. Further, these differences should be most pronounced among the smaller, more specific fields (Level 1) than the larger, more abstract fields (Level 3). Likewise, lower order neighborhoods should have greater differences in stability than higher order neighborhoods. As subgroups sizes grow, the stabilizing influence of state-embedded actors on interorganizational ties should taper as the "rules of the game" become less understood.

Triadic Clustering. For each subgroup, Table 2 reports the number of closed and open triplets, the global clustering coefficient, and the effect size expressed as an odds ratio. Supporting our hypotheses, the global clustering coefficient is significantly greater for TP relative to OWS within the Level 1 fields as well as the first and second order neighborhoods. The odds of triple closing are approximately 1.5 times more likely for TP than OWS within their Level 1 communities and 3.8 times as likely within their first order neighborhoods. Also supporting our hypotheses, the effect size decreases as the level of abstraction increases. Exempting TP's third order neighborhood, its global clustering decreases with community and neighborhood growth. Curiously, this general drop in TP's global clustering accompanies an increase for that of OWS such that its Level 3 field and third order neighborhood are 1.2 and 1.6 times likelier than TP to form a closed triplet.[3] Note that while these two figures are significant, the effect size magnitudes are smaller than those within Level 1 communities and first order neighborhoods. Given that the effect size diminishes in the proposed direction and that contradictory effects exist only within the most abstracted subgroups, we maintain that the property of triadic clustering supports both hypotheses.

Table 2. Triadic Closure within Fields and Neighborhoods

		Fields			Neighborhoods		
Level/Order	Case	Closed	Open	Cluster Coef	Closed	Open	Cluster Coef
1	TP	702	3005	0.189	594	1005	0.371
	OWS	90	580	0.134	360	2332	0.134
	X^2	11.232	***		326.592	***	
	OR	1.505			3.827		
2	TP	3171	19379	0.141	25572	123625	0.171
	OWS	231	1336	0.147	7128	38723	0.155
	X^2	0.504			63.726	***	
	OR	0.946			1.124		
3	TP	3180	19605	0.140	77571	358682	0.178
	OWS	363	1944	0.157	36954	106434	0.258
	X^2	5.317	*		4345.930	***	
	OR	0.869			0.623		

Coreness. We use two sets tests for coreness stability. The first is a difference of means test on the organizations' coreness scores, summarized by Cohen's d and σ figures to compare effect sizes.[4] (See Table 3.) On average, organizations in TP's

[3] We calculate these inversions through exponentiating the absolute value of the log of the reported odds ratios.

[4] The degrees of freedom follow Welch's approximation to avoid equal variance assumptions between cases. The results are substantively the same using pooled variance estimates.

fields belonged to 3-cores while organizations in OWS belonged to 2-cores. In terms of their neighborhoods, the organizations associated with TP typically belonged in cores ranging from four to six and OWS's neighbors usually belonged to cores up to three or four k. For all community levels and neighborhoods analyzed, the mean coreness for OWS's subnetworks is significantly less than those of TP. Referring to the standardized effects, Cohen's d and σ, these values weaken as the fields and neighborhoods grow. These findings strongly support each hypothesis.

Table 3. *k*-Core Means, Medians within Fields (by Level) and Neighborhoods (by Order)

	TP			OWS								Med Diff		
Level	Mean	sd	Med	Mean	sd	Med	t		df	d	σ	2.5%	97.5%	p(TP>OWS)
1	2.804	1.463	3	1.717	1.223	1	5.129	***	141.142	0.863	0.396	1	2	0.995
2	2.870	1.733	2	1.897	1.032	2	7.909	***	430.226	0.763	0.356	0	1	0.123
3	2.859	1.726	2	1.966	1.098	2	7.674	***	570.010	0.643	0.306	0	1	0.082
Order														
1	4.324	1.736	5	2.638	1.636	2	4.723	***	62.397	1.196	0.513	1	4	0.998
2	6.393	3.907	6	3.814	2.232	3	14.562	***	1056.633	0.896	0.409	2	3	1.000
3	4.858	3.909	4	4.059	3.442	3	7.482	***	4490.802	0.223	0.111	0	1	0.598

The second set of coreness analyses uses bootstrapped difference of medians tests. As k values are non-normally distributed, non-negative natural numbers with low mean values, nonparametric tests produce more conservative results. With replacement, we resample the coreness scores for each network and subtract OWS's median coreness scores from the median coreness scores produced by TP's networks. We repeat this procedure 10,000 times to create a distribution of test estimates. Table 3 reports the observed medians with 95% confidence intervals from these tests along with the proportion of cases in which the median coreness scores from each of TP's networks exceed those of OWS.

Within the Level 1 fields the typical coreness of TP's field affiliates differed by between one and two k values from OWS's Level 1 field. This effect did not significantly hold for Levels 2 and 3, though the probability of TP's median coreness exceeding OWS's did decline as the levels became more abstract. Likewise, assessing differences between the neighborhoods, TP's first and second order neighbors' median coreness scores exceeded those of OWS's by between one and four k within the first order neighborhoods and between two and three k within the second order neighborhood. Contrary to the second hypothesis, this effect did not weaken for the second order neighborhood, as the confidence interval narrows and a slightly greater proportion of its tests (0.2%) match the hypothesized relationship. While the median coreness score of TP's third order neighborhood typically exceeds OWS's (about 60% of the simulations), the proportion of replicated tests meeting the hypothesis fail to reach the conventional level of 95% statistical certainty.

5.5 Summary of Findings

In general, fields and neighborhoods pertaining to the Tea Party are more stable than those of Occupy Wall Street. The accuracy of this conclusion largely depends upon the level of abstraction. The most specific communities (Level 1) and the neighborhoods nearest the analyzed movements (first order) match this empirical statement very closely. The most general communities (Level 3) and farthest neighborhoods (third order) display either relatively weaker, non-significant, or contrary effects. Less certainty exists regarding the levels in between, as they did not consistently match the hypotheses. The strongest findings--that the Tea Party's closest affiliations are more stable than those of Occupy Wall Street's--holds for both operationalization of fields as well as path-based operationalizations of subgroups.

6 Conclusion

This study yields three key implications for movement scholarship. First, the study analyzes two large, interorganizational networks that include movement and non-movement organizations alike. From this study, scholars can begin to ascertain both the diverse array of organizations with whom movements regularly interact, as well as those organizations completely unaffiliated with and socially distant from movements. Following this contribution, the study furthers implore future research to examine multi-institutional politics [i.e., 4]. Further, this work also encourages researchers to assess which fields of institutional life *lack* movement organizations and seek structural explanations discerning their absence.

Second, the study approaches the media in a manner slightly different from prior social movements research. Rather than an entity which covers protests or otherwise brings attention to movement claims, here the media is an outlet that conveys relationships between organizations and structures fields. Though media coverage entails notorious selectivity effects [42], typically the coverage accurately portrays the hard facts [17]. Selectivity effects should bear limited consequences here, as this study analyzes relationship patterns rather than their frequency or representative organizational coverage. Selectivity effects aside, we have little reason to believe that national media sources systematically mischaracterize general relationship patterns between two recognized organizations in the same field. That stated, caution should be exercised in generalizing these findings to universes beyond national news outlets. Afterall, our interaction measurement only considers whether or not the Times associates two organizations with the same article. While this operationalization offers an efficient shorthand method to circumscribe fields, more refined interaction codes; such as those indicating allies, adversaries, or neutral; would provide greater generalizability.

Lastly, this study offers an innovative approach to data collection. As stated earlier, the method offers researchers a natural update to old techniques of analyzing article synopses. These benefits include offering researchers a customizable scope, resource efficiency, and accessibility. While this study analyzes only organizational networks during short time spans, other elements from the data source remain to be explored by movement and organizational scholars. These include incorporating individuals, locations, and subjects into the analyses. Dynamic organizational network analyses from similar data sources also prove a subject area ripe for movement research [e.g., 53]. Further, this study presented just one analytic example which could be conducted from such a data source. While it focused upon two movements, later studies may wish to examine the fields which circumscribe more movements and non-movements. Lastly, future research should consider integrating similar data sources with additional online references.

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