MODELING THE REPRESSION-DISSENT DYNAMIC: A NETWORK APPROACH

Abstract. Modeling the repression-dissent nexus has long been an empirical challenge, and this challenge looms large when we consider the fact that both repression and dissent comprise a wide variety of tactics imperfectly captured in standard violent-nonviolent empirical dichotomies. In this article, I introduce a network approach to model the interdependence of repression and dissent tactics as part of larger repertoires of violence. A network based on actions, rather than actors, discovers actions typically clustered together and identifies tactics triggering escalation of violence and mutual spiraling. This approach has a number of advantages over existing techniques: It captures the rather complex interplay in the repression-dissent dynamic, provides special leverage to discover the process of conflict escalation, and enables prediction of future interactions. I apply this method to two cross-national resistance event datasets and show that this network approach exhibits strong out-of-sample predictive performance. Predicting state violence also adds the important policy value of understanding when a country is about to experience major instability, so that resources can be mobilized to protect human rights.

Keywords: repression-dissent nexus, repertoires of violence, interdependence, network analysis

Dissent behaviors and state responses rarely occur independently. Accounting for their interdependence has been a central research program in the study of resistance movements and state violence. Existing work has investigated numerous ways to study the interaction, including the reciprocal effect between repression and dissent (Moore, 1998; Carey, 2006), the consequences of preventive repression on dissent (Ritter and Conrad, 2016), and exogenous factors influencing the trajectory of the interaction (Sullivan, 2016; Chenoweth and Ulfelder, 2017). Although research on the repression-dissent nexus has grown large, the bulk of existing scholarship has treated actions as if they were binary choices between violence and nonviolence. This approach fails to capture the crucial variation of tactics employed by actors, variation necessary to deliver satisfactory explanations and predictions regarding the repression-dissent nexus.[1]

This article introduces a new framework to model the repression-dissent nexus and the tactical interplay therein. I propose that the interactions between repression and dissent tactics can be conceived of as interconnected strategies the state and opposition employ, and that these interdependent strategies can be analyzed by network models. Specifically, by conceptualizing nodes as tactics and edges as co-occurring tactics employed in a resistance event, I can use network analysis to discover common patterns of tactic co-occurrence, identify the chain of action-reaction that triggers conflict escalation, and leverage the network information to predict future interactions. This framework (nodes-as-actions) overcomes the limitation of traditional networks (nodes-as-actors), where only one type of interaction is examined, and zooms in on the *repertoires of violence* to examine the hidden processes of conflict spiraling. The focus on tactics and their interactions resonates with the recent efforts in disaggregating violent actions in conflict research (DeMeritt, 2016).

I demonstrate the utility of this approach by applying it to a widely-used resistance event dataset: Nonviolent and Violent Civil Resistance Outcomes (NAVCO) (Chenoweth, Pinckney and Lewis, 2018). I conceptualize the dissent and repressive tactics that co-occurred in the same resistance event as interconnected strategies, and then utilize community detection models to discover patterns of tactical interactions between the state and the opposition. The resulting

[1] Although instrumental variable designs, such as in (Ritter and Conrad, 2016), are important to help establish causal effects, they are limited by the availability of valid instruments, the inability to understand the complex interplay of the actions, and an inability to contribute to predictive modeling.

clusters of tactics illustrate the common sequences of action and reaction between state and opposition, as well as the key actions leading to an escalation of violence. I then validate this method with an out-of-sample forecast showing that incorporating tactical dependence noticeably improves our ability to forecast types of state repression against dissidents. In other words, this network method allows improved prediction of future tactical choices, based on prior tactical patterns, a prediction vital for scholars and policymakers alike. I also find this improved predictive performance using a different dataset, Mass Mobilization Data (Klein and Regan, 2018), providing external validation of this approach.

This study contributes to the repression-dissent literature in three major ways. First, this conceptual framework goes beyond a limited binary understanding of violence by examining the full array of tactics actually used by actors. In considering the interlinked tactics, we are able to find the patterns of conflict escalation, and identify tactics that trigger further violence and potentially the conflict spiraling that previously were hard to empirically investigate. Second, this approach shows the potential to forecast which *types* of state repression against dissidents will be used, contributing to the important policy value of improving our understanding of when a country is about to experience major instability. Finally, this approach is highly scalable and can be applied to a large number of events and countries, allowing us to compare repression-dissent dynamics across different political contexts.

Modeling the Repression-Dissent Nexus

Existing Approaches. Among the state of the art, there are two separate, though related, existing approaches to modeling this nexus. The first builds on the linear assumption that governments respond to dissent and dissidents respond to government actions linearly over time (Moore, 1998; Carey, 2006). It focuses on specific sequences where violence or nonviolent protest led to state repression and analyzes what followed that repression. Since time matters in interpreting this relationship, common tools include sequential modeling, vector autoregressive models, or other variants of simultaneous equation methods with the goal to uncover the reciprocal pattern. The second approach moves in a different direction by analyzing preemptive repression and dissent. Research pushes against the linear assumption by the logic that if we believe governments respond rationally to incentives and dissidents do the same—meaning the strategic choices are endogenous—then we should expect they internalize the costs or benefits of their opponents' expected behavior *ex ante* into their strategic calculations. Using an instrumental variable design to address the potential unobservability, Ritter and Conrad (2016) find no clear association between repression and dissent after accounting for preemptive repression.

While these approaches have built the foundation of the literature, a critical but underanalyzed factor in the repression-dissent nexus is the interactive *repertoires of violence*. Empirical analyses often fall short of accounting for the critical variation of tactical choices. To fit the multiple equation models or instrumental variable models, the observations usually need to be compressed to a binary or indexed representation, which sacrifices important information on the tactical choices employed by the actors involved. This practice is problematic because dissidents often use a variety of tactics such as protests and demonstrations, destroying property, attacking police, and killing government personnel; likewise, governments use a range of repressive strategies such as mobilizing police, threatening to disperse, arresting protesters, and assaulting or killing dissidents. Dichotomizing the actions into simple violent-nonviolent categories omits a host of useful information necessary to understand strategy shifts, substitutions, and pathways to conflict escalation.

A New Network Approach. Traditionally, network analysis has been applied to study the web of *actors* where actors are nodes and their connections are edges. This actors-based network is useful when researchers are interested in varying combinations of actors based on a specific type of interaction. However, it only represents one way of conceptualizing connections and limits the analytic power of networks when researchers are interested in modeling multiple types of interactions between a set of actors. To address this issue, I propose a conceptual alternative in which nodes are represented as types of actions and edges are the *co-use* or *co-occurrence* of actions. This re-conceptualized framework becomes powerful in studying tactical interplay and examining patterns to potentially observe conflict escalation and deterrence. A growing body of research has recognized the analytical utility of different conceptualizations of networks.[2] To

[2] Chyzh and Kaiser (2019) conceptualize nodes as edges and use networks of edges to estimate the ideation space in legislative alliances. Fariss and Schnakenberg (2014) conceptualize human rights violations as a mutually dependent network. Cunningham, Dahl and Frugé (2017) study tactical diffusion between dissident groups by

the best of my knowledge, this is the first attempt at applying an action-based network to study the repression-dissent dynamic.

Application

Data. I apply this network approach to a widely-used resistance event dataset (NAVCO v3.0) to analyze tactical interplay in resistance events. It is one of the few datasets that provides a cross-national survey of nonviolent and violent methods employed by the state and the opposition at the micro-event level and thus offers analytical advantages over other existing datasets, such as the Social Conflict in Africa Dataset (SCAD) and the Armed Conflict Location and Event Data (ACLED), where methods of contention have not yet been documented. NAVCO v3.0 assembles over 100,000 hand-coded observations of nonviolent and violent methods in 25 countries around the world between 1991 and 2012. The human coding process also yields higher accuracy relative to machine-coded event data. The main coding structure follows the *Source-Action-Target* format, so actions from governments or from dissidents targeting each other are recorded for each event. CAMEO ontology was applied for action coding and encompasses twenty action types (Schrodt, 2012), from extremely cooperative/accommodative—such as *cooperate, aid, and yield*—to highly conflictual and violent events—such as *arrest, assault, and kill*.[3] This allows examination of various tactic repertoire used by both sides. Summary statistics of the events and tactics are in Appendix Figure A.1 and A.2.

Converting Tactical Data to Action-Reaction Networks. Dissent and repressive tactics that co-occurred in the same resistance event are coded as interconnected strategies, which allows me to identify behavioral patterns for the state and dissidents. In v3.0 data, an event is defined by having the same *story title*, same *provincial location*, and same *set of actors* between the government and the opposition, so action and reaction are ensured to match together. Considering co-occurring tactics as interdependent strategies is a practice oft-used in the literature studying strategy interdependence (Ring-Ramirez, Reynolds-Stenson and Earl,

treating the entire movements as a connected network. Sociologists, such as Ketchley (2017), use network graphs to qualitatively map the connections between protest locations.

[3] Since I am primarily interested in the action-reaction dynamic, non-action events (either state's or opposition's reactions are missing) are not considered. But one may be interested in the action-reaction-inaction triple relationship; in this case, we can conceptualize non-action as a special type of reaction and encode the dyadic relationship in the network.

2014; Fariss and Schnakenberg, 2014). Fariss and Schnakenberg (2014), for example, code the co-occurring human rights violations recorded by CIRI human rights report in the same country-year as interlinked strategies. In v3.0 data however, co-occurrence is coded at the event level which is more appropriate given that state actions and dissent responses specifically target each other, and event level co-occurrence also allows for discovering patterns at a more micro level. Here is an event example listing the methods used in clashes between the Berber minority (opposition group) and the Algerian government, as documented in v3.0 data:

Story title: Clashes as police prevent Berber march in Algeria (Tizi Ouzou, 2002-07-25)

- D_protest: "Demonstrators marched in defiance of a ban on a planned protest march."
- D_protest: "Meanwhile, a general strike called by the traditional Berber leaders was widely followed in Tizi Ouzou, where virtually all shops were shuttered."
- D_clash, G_clash, G_disperse: "On the western edge of Tizi Ouzou, security forces clashed with protesters ...; Skirmishes also broke out near a theater ...; Police used tear gas to disperse groups of marchers ..."
- G_mob police: "Police were deployed heavily around Tizi Ouzou."

In this event, a list of observed actions are documented and categorized in CAMEO verb types, and these tactic interactions can be conceived as an interdependent network. However, there is no clear sequence among the actions. The unidentifiable sequence of actions is very common in event data because they are difficult to code in news reports and tend to generate high error rate if a sequence is enforced (Klein and Regan, 2018). While action sequences could be derived in multi-days events, the majority of protest events are one-day events across major event datasets, which increases the difficulty of extracting sequential information. The action-network approach helps to accommodate the lack of sequential reporting by accounting for tactical association and linkages even though the causal sequence is missing.[4] In the subsequent section, I will show that tactical association proves useful in predicting state violence even without clear causal direction.

Finding Clusters in Action-Reaction Networks. To explore the tactical network structure, I employed one of the most commonly used modularity-based community detection methods introduced by Newman (2004). Since my goal is to generate clusters within the network,

[4] If sequential information of tactics is specified in the data, tactics interplay can be simply transformed to a *directed* action-network, in contrast to an *undirected* action-network shown here, and the same analysis (e.g. community detection) can be applied.

the community detection model is a natural choice. Community detection has the strength of partitioning a network into stable subgroups by considering which groups of nodes interact more strongly within themselves than outside of themselves. The idea behind it is to compare the links within each of a proposed set of communities to that between those communities and then choose the set of communities that maximizes weighted links within communities while minimizing those between communities. Since this method provides a principled way of discovering subgroup structure from rather complex networks and does not require pre-specifying a number of clusters, it has attracted wide applications in recent literature (Cranmer, Menninga and Mucha, 2015; Beardsley et al., 2019).

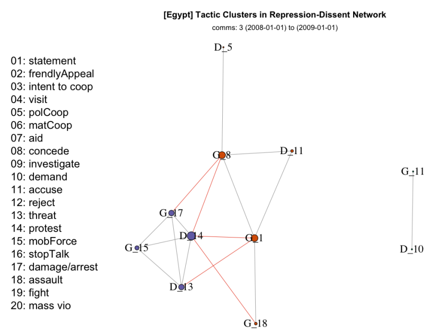
Example Clusters. Figure 1 presents two illustrative examples of networks using Egypt data where resistance actions and state responses show considerable variation, one in 2008 (left) and the other in 2011 (right). The node colors represent their cluster membership and node sizes indicate their degree of connections in the network.[5] These two networks display different combinations of tactic choices and patterns of conflict escalation and de-escalation during resistance movements. For example, if we examine the cluster with protest actions (D_14) (in which many researchers are interested), some interesting features stand out. In 2008 the clustering shows that nonviolent protest actions (D_14) were often associated with police mobilization (G_15) and arrest/disperse (G_17) without escalating to higher level violence from either side. This suggests that the government's coercive strategies such as police mobilization and crowd dispersal seem effective in diffusing conflict during that time. Escalation was more likely to have been prevented by the state's deterrent strategies.

In contrast, the cluster of protest tactics shows a different pattern in 2011 when a national election occurred along with a wide-spread resistance movement. Here, nonviolent protest tactics were associated with more violent state responses such as arrest (G_17), assault (G_18) and killing resistants (G_19); the tactics involving greater repressive violence are also clustered with more violent dissenting actions such as damaging properties (D_17) and even killing government personnel (D_19). The action-reaction pattern shifted away from a low-level nonviolent

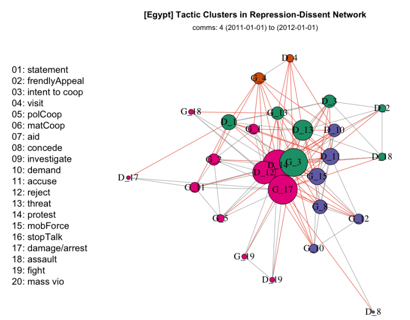
[5] The prefix (G) denotes state actions while (D) denotes dissent actions. More summary statistics for these networks are in the Appendix Table A.1 and Table A.2.

response equilibrium and escalated to more violent interactions from both sides. Conflict defusing mechanisms such as police mobilization and crowd dispersal failed to work as they had in 2008 and did not prevent escalations, even with other conciliatory moves from the government. These examples show that the action-reaction network allows us to derive associations between co-existing tactics, distinguish patterns of violent and nonviolent interactions, and identify key tactics contributing to escalation of violence and mutual spiraling.

Figure 1. Action-Reaction Networks



(a) Egypt: 2008



(b) Egypt: 2011

Predicting State Repression

In this section, I demonstrate the value of this network approach by testing its predictive power. If the logic of conflict escalation and how it relates to the interplay between tactics is correct, we should expect to see a better prediction of future tactics by incorporating information on prior interactions because they follow each other.

For predictive analysis, I separate the event data into two sets: training vs test sets. The dataset contains events from 1991 to 2012. I followed common partition practice by excluding the last few years (2010-2012) of observations as my test set and estimated my model using the previous years. The unit of analysis is at the event-dyad level,[6] so I can predict which types of repression tactics are likely to co-occur with the observed dissent tactics. This empirical framework aids me in answering an important policy-relevant question: if we observe a protest,

[6] For example in an event A, we have known that dissidents go on the street to protest against the government (D_14); then data will list all possible government responses (from G_1 to G_20) which then shows 20 combinations between the protest tactic and the co-occurring repression tactics to predict.

how should we expect the state to respond, or more specifically, what *types* of responses can be predicted?

Since I am predicting tactical dyads, the outcome variable is the repression tactics used against the observed dissent tactics in each event. The main predictors are the network variables that include both group-level information (e.g., the community assignments of the tactic) and node-level information (e.g., different centrality measures of the nodes). Centrality captures the structure of the network that indicates which nodes are the most connected (degree centrality), bridge different groups of nodes (betweenness centrality), have access to the most important nodes (eigenvector centrality), and have shortest linkages (closeness centrality) to the rest of the nodes. Communities and centralities in the tactic network combined render key information on connectedness I need to predict co-occurrence. All the network variables are lagged for one year (using events 12 month prior the predicted event) to discover patterns of prior interactions, with robustness checks done at 3, 6, and 9 monthly lags shown in Appendix, Figure A.3, A.4 and A.5.

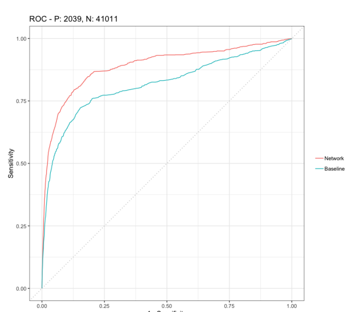
I incorporate a number of covariates considered important in predicting repressive violence in existing literature. First, at the tactical level, the model incorporates symmetric pairs of tactics as a proxy for the finding that violence begets violence (reciprocity effect)[7] and also a dyadic lag of tactics to account for underlying temporal dependence. Second, the model includes event features recorded in the v3.0 dataset such as campaign goals and the number of participants. I added structural variables that may influence repression choices such as the total population of the country, the GDP growth and whether there were elections or civil wars taking place in the country. I also consider regime types by including a PITF democracy indicator, civil liberties index, and regime durability. For comparison, two models are estimated from the logistic regression: the baseline model has only the standard predictors, and the network model adds the network variables.[8]

Out-of-sample Prediction Results. The main results are shown in Figure 2, where the performance of the network model is compared against the baseline model. The ROC curve

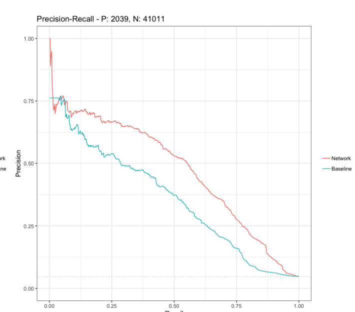
[7] For example, if dissidents use D_18 (assault), the use of G_18 (assault) by the government is expected.
[8] The in-sample coefficient estimates are reported in Appendix Table A.3.

shows that the network model clearly improves prediction: networks generate nearly 91% correct predictions whereas the baseline model generates around 81% correct predictions (also shown in Appendix Table A.4). But since violence is rare, a good AUC score in the ROC curve could mean the model is just good at capturing zeros in the observations. A way to look at this is precision and recall. The Precision and Recall curve in Figure 2 shows that the network model also outperforms in terms of predicting ones (the actual occurrence) when considering violent interactions are rare events. Figure A.6 in the Appendix provides another visualization of prediction results via a closer examination of one of the key pairs (Protest vs. Arrest). This time-series plot shows that the trend of prediction also matches closely with the underlying growth in the out-of-sample data setting.

Figure 2. Out-of-sample Prediction, Network Lag: 12 Months (2010-2012)



(a) ROC Curves



(b) PR Curves

Robustness. Additional efforts are made to validate the results. First, I divide data into two subsets, eventful and eventless sets, to see if the results are sensitive to the number of observations in the data. Second, I apply the same approach to a new dataset, *Mass Mobilization Data*, to show external validation of this approach. They are detailed in the Appendix Section 1 due to the space constraint, but both support the validity and utility of my approach.

Conclusion

Understanding the interactive effect between repression and dissent has long been an important agenda in conflict studies, but it also presents an empirical challenge for researchers to explore the interdependent dynamics. Using micro-level event and tactic data, I introduce an action-based network approach to study tactical interplay, identify tactics often used together, and examine patterns of conflict escalation and deterrence. Overall, the applied Louvain community detection model combined with centrality measures provides special leverage to analyze the interactive repertoires of contention that are understudied in the current literature. Predicting state violence also adds the policy value of understanding when a country is about to experience major instability, so that resources can be mobilized to protect human rights or threats to legitimate governance.

The application of this approach opens up a host of new research to explore. New event and tactics data combined with this network approach provides a new framework to study the processes of conflict escalation in a more interactive manner. For example, the electoral violence literature suggests that elections incentivize violence from both the incumbent and the opposition, but what tactics tend to stimulate violent reactions or deter further escalation remain unanswered. With this new tool, we can inspect tactics and their interaction and unpack the processes of conflict spiraling. The potential of the network approach is perhaps even stronger as an explanatory variable. Future work can apply this framework to explain when repression-dissent violence will lead to more turbulent armed civil war or revolutionary momentum for regime transition.

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Modeling the Repression-Dissent Dynamic: Online Appendix

Appendix

Table A.1: Same Community for Protest Tactic (Egypt 2008)

tactics	comm	algor	modul	degree	between	close	eigen	memberN	year	country
D_protest	3	multi level	0.23	6	0.00	0.03	1.00	4	2008	Egypt
D_threat	3	multi level	0.23	4	3.50	0.03	0.31	4	2008	Egypt
G_arrest	3	multi level	0.23	4	2.50	0.03	0.94	4	2008	Egypt
G_mobForce	3	multi level	0.23	3	0.50	0.02	0.37	4	2008	Egypt

Table A.2: Same Community for Protest Tactic (Egypt 2011)

tactics	comm	algor	modul	degree	between	close	eigen	memberN	year	country
D_damage	4	multi level	0.14	3	0.28	0.02	0.02	11	2011	Egypt
D_kill	4	multi level	0.14	4	0.45	0.02	0.08	11	2011	Egypt
D_protest	4	multi level	0.14	24	8.14	0.02	1.00	11	2011	Egypt
D_reject	4	multi level	0.14	18	26.24	0.02	0.35	11	2011	Egypt
G_accuse	4	multi level	0.14	8	7.95	0.02	0.11	11	2011	Egypt
G_arrest	4	multi level	0.14	23	50.94	0.02	0.87	11	2011	Egypt
G_assault	4	multi level	0.14	4	0.40	0.02	0.08	11	2011	Egypt
G_frendlyAppeal	4	multi level	0.14	9	4.44	0.02	0.14	11	2011	Egypt
G_kill	4	multi level	0.14	4	0.00	0.02	0.10	11	2011	Egypt
G_polCoop	4	multi level	0.14	6	0.58	0.02	0.13	11	2011	Egypt
G_statement	4	multi level	0.14	8	2.35	0.02	0.19	11	2011	Egypt

Table A.3: Dyadic Model: Predicting State Responses to Protest (1991-2009)

	Dependent variable:	
	Tactics Dyad	
	Network	Baseline
Campaign Goals	−0.004	−0.020
	(0.025)	(0.023)
Num Participants	0.021	0.011
	(0.017)	(0.016)
Leader Tenure	−0.039	−0.041*
	(0.025)	(0.023)
Discrimination	−0.021	0.002
	(0.028)	(0.025)
Ln Population	−0.122***	−0.164***
	(0.036)	(0.033)
Ln GDP percap	0.014	−0.091***
	(0.029)	(0.027)
Regional Campaigns	0.095	−0.060
	(0.071)	(0.065)
Election	−0.013	0.053**
	(0.024)	(0.022)
Regime Durability	0.132***	0.160***
	(0.041)	(0.038)
Civil Liberty Index	0.056	−0.023
	(0.045)	(0.042)
Coup in past 5yr	0.062***	0.005
	(0.022)	(0.021)
Democracy	−0.004	−0.086**
	(0.040)	(0.037)
Dyadic Lag	0.491***	2.085***
	(0.047)	(0.041)
Symmetric pairs	0.182***	0.147***
	(0.017)	(0.016)
sameComm	0.320***	
	(0.026)	
between_G	−0.011	
	(0.024)	
degree_G	0.186***	
	(0.042)	
eigen_G	0.590***	
	(0.028)	
close_G	0.068***	
	(0.017)	
sameComm:between_G	0.011	
	(0.009)	
sameComm:degree_G	−0.155***	
	(0.017)	
sameComm:eigen_G	0.041***	
	(0.012)	
sameComm:close_G	−0.025***	
	(0.006)	
Constant	−3.584***	−3.208***
	(0.041)	(0.035)
Observations	66,570	66,570
Log Likelihood	−8,261.517	−9,725.422
Akaike Inf. Crit.	16,571.030	19,480.850
Note:		*p<0.1; **p<0.05; ***p<0.01
		Standard errors clustered at the country level.

Figure A.1: NAVCO v3.0: Events in Countries

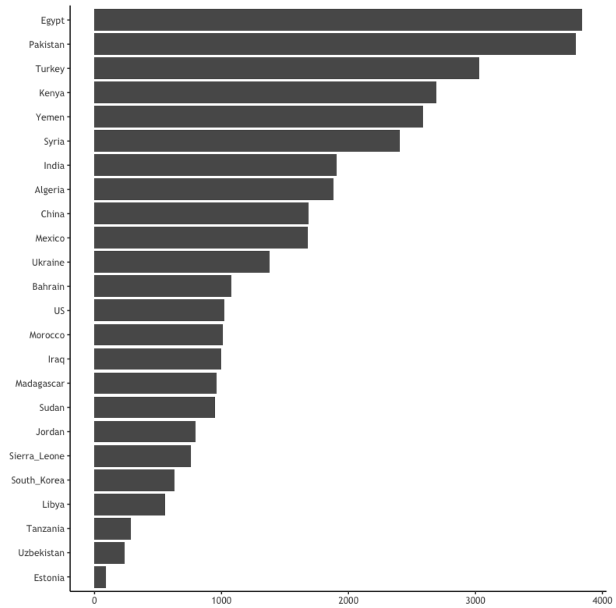


Figure A.2: NAVCO v3.0: Tactics

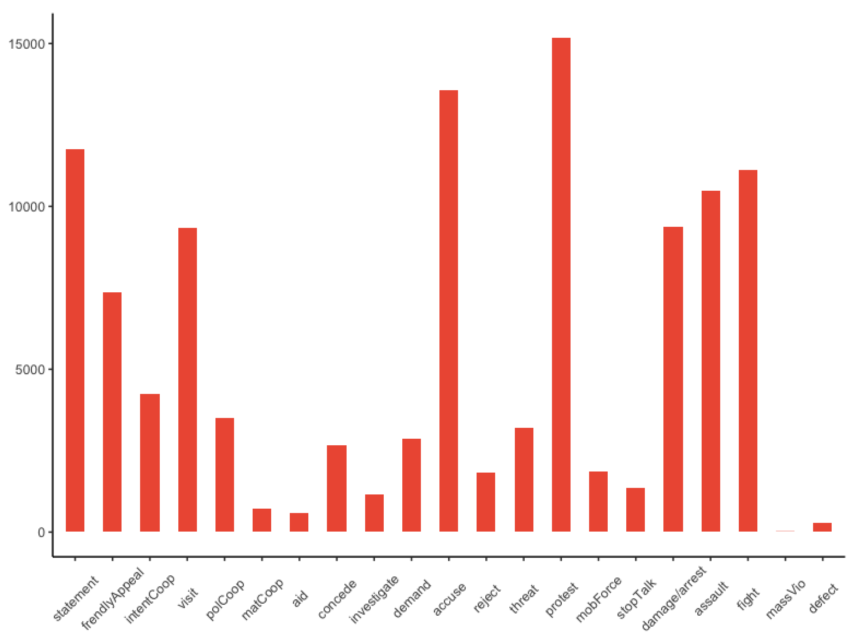


Figure A.3: Out-of-sample Prediction: 2010-2012 (3 month lag)

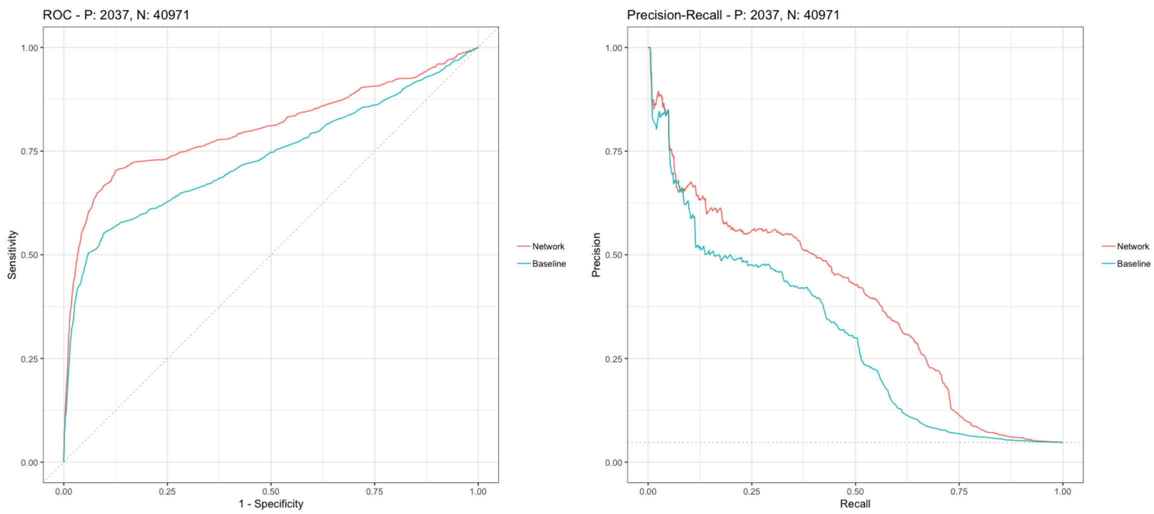


Figure A.4: Out-of-sample Prediction: 2010-2012 (6 month lag)

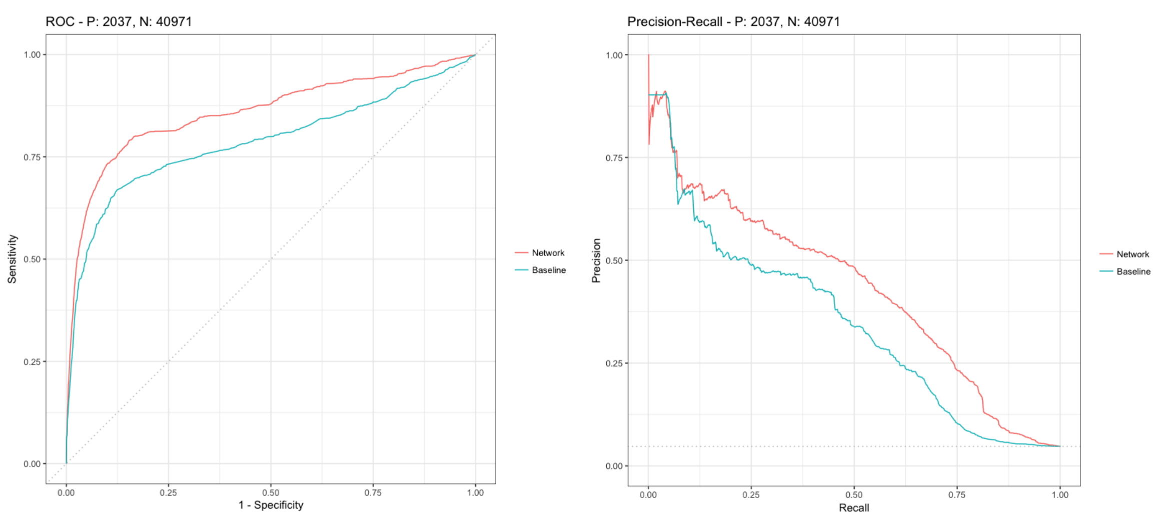


Figure A.5: Out-of-sample Prediction: 2010-2012 (9 month lag)

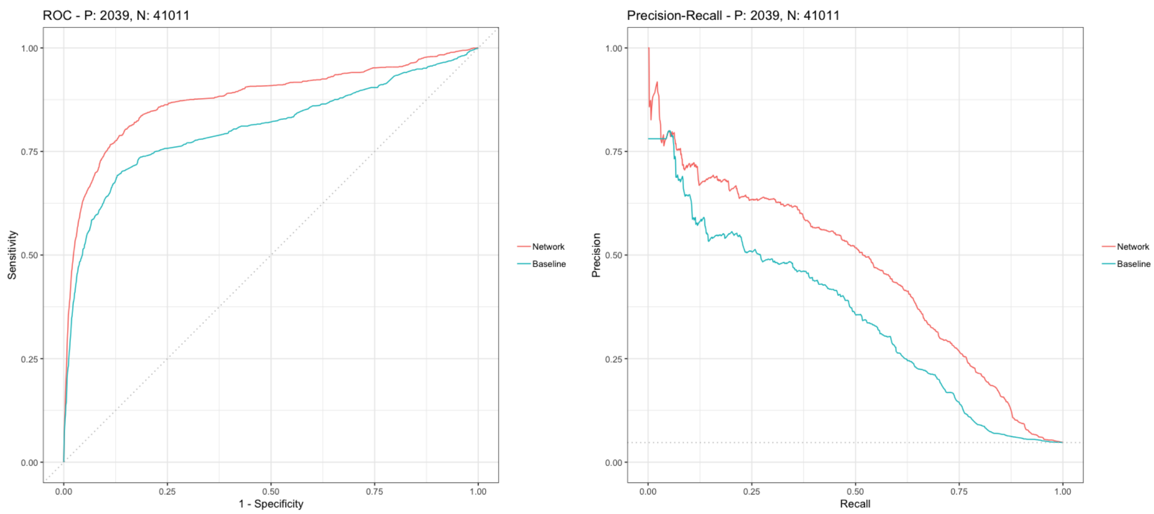


Figure A.6: Out-of-sample Prediction: Protest vs. Arrest

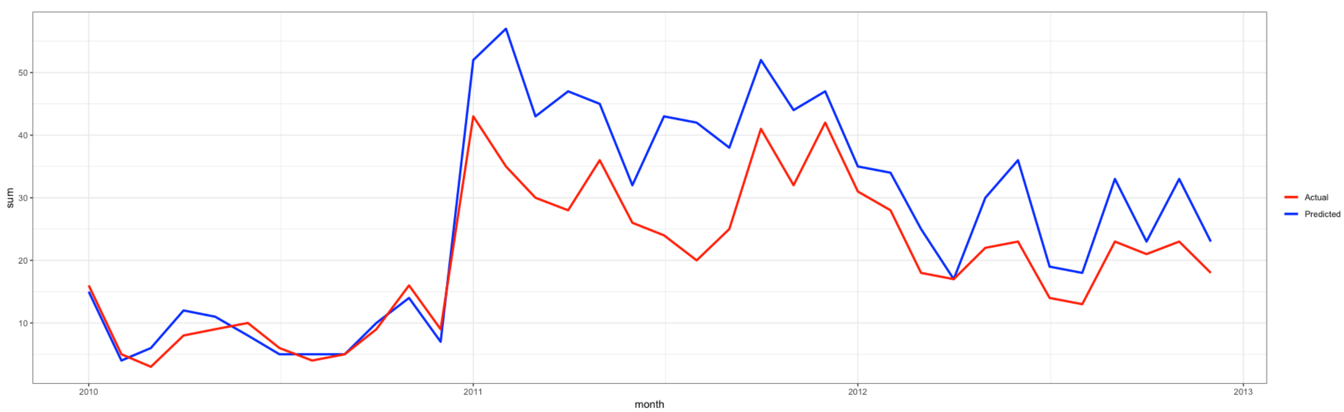


Table A.4: Forecast Performance for Predicting State Responses, Network Lag: 12 Months (2010-2012)

	Network	Baseline
AUC	0.9070	0.8089
Accuracy	0.9591	0.9496
Precision	0.5877	0.4619
Recall	0.4605	0.3864
Brier	0.0323	0.0449

1 Robustness Checks

Additional efforts are made to validate the results. First, due to the need of intensive human coding effort, the v3.0 dataset currently does not have a representative country coverage in the world and oversamples from the Middle East and Africa because of the interest in studying dissent-repression methods. While predictive performance is not necessarily sensitive to country samples because it is evaluated at the out-of-sample testset, it could generate implication on generalizability and a concern that this network approach could only predict well in eventful countries where more conflict and more tactics are observed. To address the concern, I divided the data into two subsets: eventful and eventless sets. The eventful set represents the half of the countries (13 countries) with more events documented while the eventless represents another half of countries (12 countries) with fewer events. The eventless set can thus be seen as a hard test for my prediction. Figure A.7 shows that prediction is not influenced even though there are fewer events to forecast. The network model is capable of predicting tactics in different event sample size.

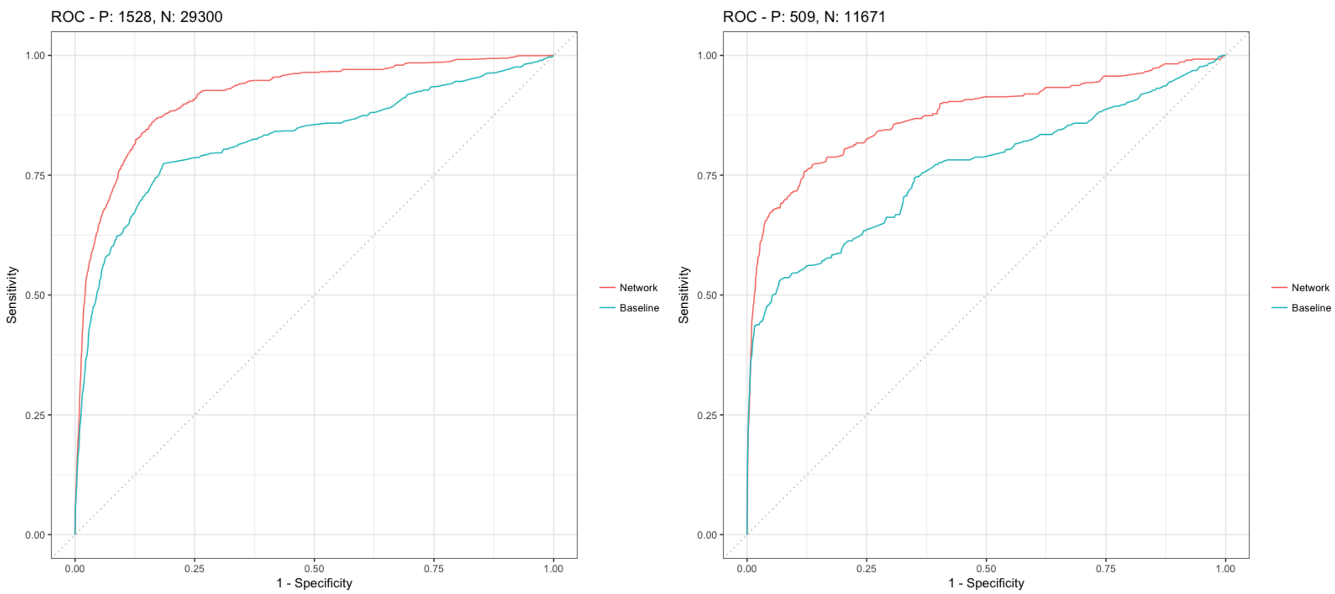
Second, I apply the same approach to a new dataset: *Mass Mobilization Data*. It is built to study disaggregated interactions between protesters' demands and state responses, making it a good second testset for the network approach. The dataset covers 162 countries, a wider range than NAVCO, from 1990 to 2014. It also clearly maps repression tactics against dissent demands in each event, so I can code the co-ocurrence in the same way as it is done when using NAVCO v3.0 dataset.[1] While this mobilization data were designed to ask a slightly different question: how protesters' demands interact with state responses, the interactive structure of the demands-responses is highly applicable for the proposed network framework. Following the exact same forecasting procedure and variables, the prediction result in Figure A.8 and Table A.5 again shows a clear predictive improvement over the baseline model, which provides external validation to the network approach and demonstrates

[1] Protesters can make multiple demands (up to seven types), and state can respond in multiple ways (up to seven types). Data statistics and visualization are available here: `https://www.binghamton.edu/political-science/massmobilization.html`

Figure A.7: Out-of-sample Prediction: 2010-2012 (Eventful vs Eventless)

(a) Eventful Subset

(b) Eventless Subset



the generalizability of the method to study dynamic actions.

Table A.5: Forecast Performance Using Mass Mobilization Dataset, Network Lag: 12 Months (2012-2014)

	Network	Baseline
AUC	0.7603	0.7089
Accuracy	0.8133	0.8076
Precision	0.5667	0.5245
Recall	0.1910	0.1668
Brier	0.1343	0.1445

Figure A.8: Out-of-sample Prediction Using Mass Mobilization Data: 2012-2014 (12 month lag)