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Using ERGMs to Disaggregate Displacement Cascades*

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Abstract

How do civilians select internal displacement destinations during conflict? Existing research emphasizes the value of cascades as a guide to making these difficult decisions. Cascades may involve civilians following people in their social networks (community cascades), people with similar characteristics (co-ethnic cascades), or the crowd in general (herd cascades). Analyses relying upon interview or regression-based methodological approaches face substantial challenges in identifying the prevalence of, and relationship between, each type of cascade. While interview-based approaches can incorporate location characteristics and movement patterns, they struggle with assessing aggregate trends. Meanwhile, regression-based approaches can assess aggregate trends, but they struggle with incorporating location characteristics and movement patterns. Exponential Random Graph Models (ERGMs) that conceive of locations as nodes in a network and movements between those locations as ties can overcome these challenges and assess aggregate trends while incorporating location characteristics and movement patterns. This paper demonstrates the utility of this approach using data from UNHCR on internal displacement in Somalia from 2007-2013. Results reveal that herd cascades only form at high displacement levels, co-ethnic cascades form at medium and high displacement levels, and community cascades form at all displacement levels. Therefore, cascades provide stronger guides for displacement-related decisions as civilians switch from following the crowd in general to following those with similar characteristics to following social ties.

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I. Introduction

As refugee crises, most notably the Syrian refugee crisis, have captured the concern of governments worldwide, internal displacement is often overlooked. Yet, according to estimates from the International Organization of Migration (IOM), there are now approximately 20 million refugees (external displacement) worldwide, while there are approximately 40 million internally displaced people (IDPs) (UNHCR, 2015c). These internally displaced people concern host communities due to their increased likelihood of engaging in violent collective action, aggravating food insecurities, increasing housing prices in host communities, and facilitating conflict diffusion (Corps, 2012; FSNAU, 2015; Salehyan, 2011). Syria is currently the most infamous example of these dynamics. While its 4 million refugees are widely covered in international media, its 8 million IDPs receive far less coverage, despite facing conditions that are arguably more severe (Martinez and Eng, 2016). Large-scale internal displacement also affects many African countries, such as Libya, South Sudan, Central African Republic, Democratic Republic of Congo, and Somalia.

As observers attempt to understand the processes driving internal displacement, there is a popular image of civilians fleeing for their lives from massacre. However, recent research shows that civilian decision-making incorporates considerations of a broad array of social, economic, geographic, and political factors, as well as expectations about conflict dynamics and potential threats (Schon, 2015; Rubin and Moore, 2007; Uzonyi, 2014). This decision-making produces patterns in displacement destinations. There is a wealth of scholarship examining patterns in refugee movement (Ruegger and Bohnet, 2015; Moore and Shellman, 2006; Moore and Shellman, 2007). To improve explanations of these patterns for IDPs, this paper asks how civilians select their internal displacement destinations.

Civilians weigh many factors while making decisions about their displacement while navigating a confusing information environment, in which it is difficult to distinguish fact from fiction (Schelling, 1981). This makes the act of interpreting existing information crucial, as well as extremely difficult. Facing this challenge, people often follow the behavior of others and form cascades, especially when the decision is risky (Göbel, 1998). Cascades result from the transformation of heterogeneous individual preferences and characteristics into group action (Granovetter, 1978). Civilians observing the formation of cascades can then use them as guides to interpreting existing information, thereby shaping their displacement decision-making. Such behavior is frequently documented in contexts with large-scale population movements, leading to the development of labels such as 'chain migration' (Davenport et al., 2003; Moore and Shellman, 2006; Ruegger and Bohnet, 2015; MacDonald and MacDonald, 1974).

Cascades can involve different types of groups. Some argue that civilians move in herd cascades, converging on the same locations as other civilians that moved before them, regardless of whether these civilians have personal ties (Banerjee, 1992; Bauer et al., 2002; Epstein, 2008). Other scholars argue that civilians move in co-ethnic cascades, converging on co-ethnic locations (Ruegger and Bohnet, 2015; Steinberg, 2015; Bartel, 1989). Still, other scholars argue that civilians move in community cascades, converging on the same locations as their friends and family members (Rawlence, 2016; Epstein, 2008). However, we researchers often lack the ability to directly compare the patterns in how these types of cascades influence displacement destinations.

This challenge comes from the inherent limitations of interview and regression-based approaches to the study of migration. Interview-based approaches can effectively incorporate location characteristics, including origin, transit, and destination locations, and movement patterns into nuanced analyses. Such analyses have been crucial for explanations of the transnational dynamics of migration (Horst, 2006; Whitehouse, 2012), remittance behavior (Lindley, 2010a), and for uncovering important mechanisms in the process of migration (Kane, 2013). However, they are often unable to assess broader correlations and aggregate migration trends. Regression-based approaches can effectively assess aggregate migration trends (Czaika and Haas, 2014), but their requirement of using variables from a single level of analysis forces them to focus on location characteristics or movement patterns. They cannot fully incorporate both.

Social network analysis, therefore, presents a valuable alternative. Migration scholars usually use social network analysis to examine networks of individuals and their relationships with each other. I apply social network analysis to examine networks of locations and internal displacement flows between those locations. This shift allows me to examine how people incorporate information about locations, and movements between locations, into their decisions of where to move.

After conceiving of locations as nodes in a network and displacement movements between those locations as ties, Exponential Random Graph Models (ERGMs) can incorporate both of these elements into a single quantitative analysis to consider aggregate trends in displacement. Internal displacement data from Somalia that tracks the origin and destination locations of each internal displacement movement facilitates this analysis (UNHCR, 2007). Network covariates that can be modeled with Exponential Random Graph Models (ERGMs) can then directly measure each cascade type: ethnic homophily for co-ethnic cascades, preferential attachment for herd cascades, and transitivity for community cascades (Cranmer and Desmarais, 2011; Wasserman and Faust, 1994; Maoz, 2010).

Through ERGMs with thresholds for ties set at 1 person (Unweighted), 324 people (25^{th} percentile of displacement movement magnitudes), 835 people (50^{th} percentile of displacement movement magnitudes), and 2622 people (75^{th} percentile of displacement movement magnitudes), it is then possible to detect patterns in the presence of each cascade type.[1] These thresholds are arbitrary. The primary goal was to set several different threshold levels based on clear, objective criteria.

Findings indicate that each cascade type forms at different thresholds. Herd cascades form at the 50^{th} and 75^{th} percentile of displacement movement magnitudes. Co-ethnic cascades form at the 25^{th} percentile and above. Community cascades form at all displacement levels. This provides evidence as to when civilians use each cascade type as a guide. It supports the view that, when possible, civilians use the behavior of their social ties as guides. As displacement levels increase,

[1] In this paper's analysis, these thresholds will be referred to as Unweighted, 25^{th} percentile, 50^{th} percentile, and 75^{th} percentile.

the resultant confusion can make social ties difficult to track, so civilians resort to shared ethnicity as a Plan B. Even higher displacement levels can make the actions of others with shared ethnicity difficult to track, so civilians resort to following the crowd as a Plan C. This preference order can only be detected by disaggregating cascade models, and it reveals a key civilian preference order for following social ties, then co-ethnics, and then the crowd in general.

This paper will begin by explaining the complexity involved in civilian displacement decision-making. This complexity arises from the many factors civilians must weigh, as well as the uncertainty regarding the accuracy of available information about those factors. Responding to complexity, civilians use displacement cascades as a guide to interpreting available information. Then, this paper will specify three types of cascades: herd cascades, co-ethnic cascades, and community cascades. ERGMs using UNHCR data on Somali internal displacement movements facilitate an analysis of the patterns of each cascade type. Finally, the paper concludes with directions for future research on displacement and how other areas of contentious politics research may evaluate the roles of each cascade type.

II. The Complexity of Civilian Decision-Making about Displacement

Civilian decision-making about displacement weighs many social, economic, geographic, and political factors. Socially, civilians must consider the needs of their own families and households. Personal networks can provide the necessary resources for civilians to avoid movement, or they can make movement easier. They can also make certain displacement destinations more desirable (Harpvicken, 2009). Economically, civilians need the financial resources to move. At the same time, they must also weigh the economic conditions of their origin location and the economic conditions of their destination location (Adhikari, 2013). Geographically, civilians must consider the distances that they must travel and the types of terrain that they must navigate (Moore and Shellman, 2006). Politically, civilians must consider the level of physical threat that they face (Davenport et al., 2003). This combination of considerations can be extremely difficult to weigh.

Thus, during conflict, civilians find it valuable to monitor as much information as possible about violence and wider conflict dynamics. This information can take many forms, such as media reports, rumors, conspiracy theories, signals, and experiences. Often, this information is unverified and may be distorted in numerous ways (Allport and Postman, 1947; Shibutani, 1966). The sum of all of this information forms a confusing information environment, in which it is difficult to distinguish fact from fiction.

This confusing information environment requires civilians to find ways to interpret information, so that they may weigh the social, economic, geographic, and political factors that affect their decision-making about displacement. Facing this challenge, people often follow the behavior of others and form cascades. Cascades form when people with heterogeneous individual preferences and information choose to engage in group action (Granovetter, 1978). This is particularly common when civilians have to make risky decisions (Göbel, 1998). Cascades form because they offer civilians a guide with which to interpret information and make decisions (Banerjee, 1992).[2]

Cascades do not necessarily drive each movement during the displacement process. Instead, they drive the selection of final destination locations. This is important, as displacement often includes multiple movements. Each movement can involve new decisions (Karen Jacobsen and IDMC, 2008; Triandafyllidou and Maroukis, 2012). Several factors make displacement a process that involves multiple movements. First, checkpoints and violence along roads motivate civilians to use different routes (Lubkemann, 2008; Singer and Massey, 1998; Lombard, 2013). Second, varying levels of access to transportation lead to variation in when and where civilians are able to move (Brachet, 2009; Steinberg, 2015; Triandafyllidou and Maroukis, 2012). Third, households divide during the displacement process, motivating civilians to reconnect as soon as possible (Horst, 2006).

Moreover, the desire for physical safety tends to drive the first movement in the displacement process. Civilians pursue other concerns, including economic prosperity, after physical safety is achieved (Metcalfe et al., 2012; Lauten and Kesmaecker-Wissing, 2015; Ferris, 2014; Drumtra, 2014). As one Somali refugee comments, “When you flee your home, the only thing on your mind is safety. You keep moving until you find some place that is safe. Only when you have safety do you think about other factors, such as employment, health care, and food” (Author interview in Columbus, Ohio, in May 2015).

This statement reveals another important reason for multiple movements. Displacement motivations change from one movement to another. In the common scenario that this Somali refugee describes, civilians often initially flee violence. Then, they realize that they need to keep moving in order to find a location where they can access necessities, such as jobs, health care, and food. This view of displacement asserts that individual movements have a primary motivation, but the complete journey from origin to final destination can involve many motivations. Such a multitude of motivations adds even more reasons that civilians can benefit from guides that help them interpret existing information.

III. Cascade Models

During armed conflict, cascades are arguably one of the most valuable guides for civilians. The following sections suggest a division of cascade models into three types: herd cascades, community cascades, and co-ethnic cascades. Each cascade type involves different kinds of connections between individuals involved in the cascade and different conditions under which individuals join each cascade type. Thus, rather than challenging information cascade models as a

[2] Cascades matter for both refugees and IDPs, but for different reasons. The challenges of crossing country borders often mean that refugees face greater uncertainty in selecting destination locations and how to reach those locations. IDPs are arguably more vulnerable than refugees though, as they have failed to escape the country experiencing conflict and often lack access to humanitarian aid.

whole, this paper disaggregates cascade models in order to develop more precise explanations of how civilians select internal displacement destinations.

a. Herd Cascades

Cascade models were developed primarily as models of herd behavior (Banerjee, 1992; Lohmann, 1993; Lohmann, 1994; Kuran, 1989; Ellis and Fender, 2011). When individuals are uncertain about the best course of action, they follow the behavior of others, regardless of whether social ties exist between them. As more people mobilize to participate in a given course of action, the herd behavior becomes a clearer guide about the desirability and potential for effectiveness of the action. Different types of individuals may wait for different thresholds of mobilization before choosing to participate, but observed group behavior should nevertheless increase their chances of participation. Furthermore, there may be advantages in conforming to group behavior, such as 'strength in numbers.' These mechanisms of herd behavior are commonly asserted to exist in migration processes (MacDonald and MacDonald, 1974; Schelling, 1981; Epstein, 2008). Herd behavior could, therefore, be a key driver of the selection of displacement destinations. This leads to the following hypothesis

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> H1: IDPs are more likely to move to the same locations as other IDPs, regardless of the types of social ties that exist between them.

b. Community Cascades

Alternatively, social ties may be an important driver of whether individuals choose to participate in mobilization. In particular, civilians may take their cues from community members. There are many ways to define community (Agruwal and Gibson, 1999). In this paper, community is defined as a group of people who reside in close spatial and social proximity. Friends, family members, and neighbors are the key groups within an individual's community. Community members live near each other, and they have regular social interactions. These elements of spatial and social proximity reinforce each other, as people that live close together naturally have more opportunities for social interaction (McPherson et al., 2001).

Community cascades involve civilians moving to the same destination locations as other civilians from their origin location. In particular, it involves civilians converging on the same locations as friends, family members, and neighbors from their origin location. Civilians converge by communicating as much as possible with other displaced community members (Harpvicken, 2009).

The argument that origin communities converge on the same destination locations is different from arguing that all civilians move together. As civilians become separated from each other, they often attempt to reunite. This eventually produces a convergence upon certain destination locations. If all civilians from an origin community moved together, then there would not be any need to reunite later.

Community connections can provide many important 'network externalities' to facilitate mobilization. The information, support, and resources from friendships can convince people to join rebel groups (Parkinson, 2013). Friendships in rebel groups can even provide fun, as in the case of the Muhajir Qaumi Movement (MQM) in Pakistan (Verkaaik, 2004). This insight has been applied even more broadly to protest movements and other kinds of mobilization (McAdam, 1986). Migration and displacement also draw upon these externalities from friends, family members, neighbors, and other community members (Epstein, 2008). With these considerations, this paper will test the following hypothesis.

> H2: IDPs are more likely to move to the same locations as other community members from their origin location.

c. Co-ethnic Cascades

While seeking community members, civilians may not be able to reconstitute their origin communities. Many civilians simply lose track of their origin communities as they leave their homes. This fragmentation of social ties motivates civilians to replace the fragmented social ties (Harpvicken, 2009). Such replacement social ties need to be durable and trustworthy. Short-term disposable ties may briefly provide necessary information, but they are not trustworthy enough to drive the selection of displacement destinations (Desmond, 2012).

Instead, in the midst of the instability and uncertainty of conflict, civilians often turn to co-ethnics (Habyarimana et al., 2007). In fact, a growing body of research argues that during conflict, intra-ethnic trust and generosity tend to increase (Bauer et al., 2011; Voors et al., 2012). These changes occur as conflicts instigate demographic changes, whereby areas that were ethnically heterogeneous pre-conflict become ethnically homogenous during conflict (Balcells and Steele, 2016). This is especially likely in cases of ethnic cleansing (Kapteijns, 2013). Therefore, civilians who are unable to maintain their origin communities may move to locations inhabited by co-ethnics (Whitehouse, 2012; Zilberg, 2011). This motivates the development of a third type of cascade: co-ethnic cascades.

Recent studies provide additional evidence on the role of co-ethnic cascades. In their analysis of external displacement destinations, Ruegger and Bohnet (2015) find that refugees tend to flee to co-ethnic regions. While there is insufficient data to determine whether this research on external displacement can also explain internal displacement, it does at least suggest that co-ethnic cascades merit consideration in an analysis of internal displacement. This leads to the following hypothesis:

> H3: IDPs are more likely to move to co-ethnic locations.

IV. Testing Cascade Models in the Context of Somali Internal Displacement 2007-2013

To evaluate these cascade models, I will focus my analysis on internal displacement in Somalia from 2007-2013. This time period begins with the dramatic escalation of violence resulting from the Ethiopian invasion at the end of 2006. This invasion provoked the rise of Al Shabaab in 2007 (Hansen, 2012). From that point, through 2013, conflict in Somalia has produced some of the largest internal displacement flows in the world. Between Ethiopia’s invasion at the end of 2006 and the end of 2008, roughly two-thirds of Mogadishu’s population fled the city

(Lindley, 2010b). In total, over a million people left their homes from 2007-2013, with most people moving several times (Drumtra, 2014). As one of the world's largest producers of internally displaced people, Somalia presents an important context in which to analyze how cascades influence the selection of internal displacement destinations.

Admittedly, despite the magnitude of its internal displacement crisis, Somalia contains a relatively extreme combination of characteristics. These characteristics include Somalia's nomadic traditions, state failure, foreign intervention, extreme poverty, environmental challenges, prolonged conflict, proliferation of armed groups, and clan divisions (Lewis, 2008; Aristide Zolberg et al., 1989).[3] All of these characteristics influence displacement patterns (Massey and Bohra-Misha, 2011; Massey and Silva, 2014; Balcells and Steele, 2016).

As a result, this paper's primary goal of explaining the role of cascades in Somali internal displacement has inherent policy importance. The unique combination of characteristics in the case motivates the recognition of clear scope conditions (Beach and Pedersen, 2013). Somalis, as a whole, have grown accustomed to adapting to hard times. Drought, violence, or a variety of other sources of insecurity have a history of displacing Somali civilians (Horst, 2006). In addition, nomadic traditions within Somalia help civilians respond and adapt to insecurity (Lewis, 2008). Furthermore, Somalia's weak state apparatus has provided additional impetus for Somali civilians to become adaptable and ready to respond to insecurity (Lewis, 1994). This adaptability creates the possibility that Somalis may be more adept at responding to insecurity than civilians of other nationalities. Their established methods of responding to insecurity may thus be different from the methods civilians use in other contexts. However, cascades are consistently observed throughout cases of migration and displacement. Variation between cases should at most cause variation in the magnitude of different types of displacement cascades, not whether displacement cascades form.

By focusing on the analysis of this single case, this paper benefits from the strengths of within-case analysis to build a nuanced explanation of how herd cascades, community cascades, and co-ethnic cascades influence the selection of internal displacement destinations in Somalia (Snyder, 2001). Future research could then make valuable contributions by extending and testing this explanation in other contexts.

V. Analyzing Somali Internal Displacement as a Network

To observe displacement cascades, it is important to observe civilian movements. In the aggregate, civilian movements provide the opportunity to assess the types of cascades that civilians form. These movements reveal connections between locations. This means that, by treating locations as nodes and movements as connections or ties between nodes, the system of population movements can be analyzed as a network. Social network analysis then provides a wealth of tools with which to analyze displacement patterns.

[3] Somalia's clan structure has driven clan politics to function comparably to ethnic politics in the rest of Africa (Zolberg, Suhrke, & Aguayo, 1989).

Such an analysis begins with a descriptive assessment of displacement patterns. Social network analysis provides powerful tools to track the direction of movement, locations civilians most commonly leave, locations civilians most commonly seek, and the characteristics of origin and destination locations. These components of the displacement network provide important insights into which factors civilians consider during their displacement, and thereby how cascades can guide civilians through their decision-making about displacement.

Next, Exponential Random Graph Models (ERGMs) provide the opportunity to directly measure each cascade type through network covariates and measures of different kinds of network structures. By varying the thresholds for defining a connection between locations, ERGMs can then identify whether each cascade type exists at all displacement levels.

The general equation for ERGMs can be expressed as:

$$P(Y = y) = \frac{\exp(\theta' g(y))}{k(\theta)},$$

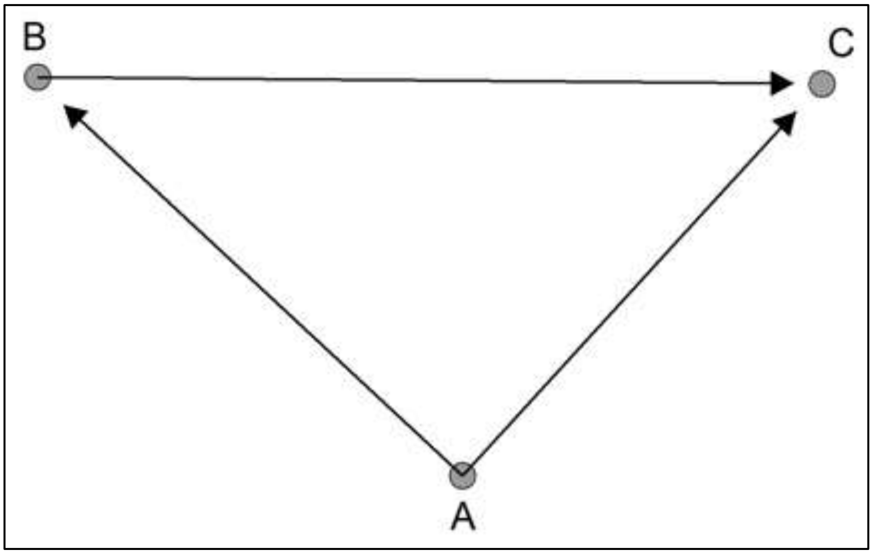
where Y is the random variable for the network state (with realization y), g(y) is a vector of model statistics for network y, θ is the vector of coefficients for those statistics, and k(θ) represents the quantity in the numerator summed over all possible networks (Wasserman and Faust, 1994).

ERGMs simultaneously allow both inference on covariates and for arbitrarily complex network structures to be modeled (Cranmer and Desmarais, 2011). Moreover, ERGMs account for dependencies between locations (nodes) and connections (ties). There are several ways to interpret ERGMs. One way involves interpretation at the network level. At the network level, the network statistics directly condition the probability of the entire network—allowing us to estimate the effect of within-network configurations on the predicted probability of observing a particular instance of the network (Cranmer and Desmarais, 2011). Simulating a large number of networks based on the ERGM parameters yields the opportunity to approximate the characteristics of the distribution of network statistics (Morris et al., 2008; Handcock and Gile, 2010). If the coefficient on a network statistic in ERGM is positive, then the observed network is likely to possess the given network characteristic.

Another way involves interpretation at the dyad level. At the dyad level, the quantity of primary interest is the likelihood of tie formation between any two nodes. In the displacement context, this means that ERGMs are interested in the likelihood of civilians moving between any two locations (Cranmer and Desmarais, 2011). If the coefficient on a dyad level statistic is positive, then that characteristic increases the likelihood of tie formation.

Finally, at the monadic level, node characteristics affect the likelihood of tie formation with specific nodes. For undirected networks, node characteristics can affect the likelihood of the node forming ties with other nodes. For directed networks, in-degree node characteristics affect the likelihood of nodes receiving ties and out-degree node characteristics affect the likelihood of nodes sending ties. This paper is interested in monadic, dyadic, and network interpretations in directed networks.

Figure 1. Transitivity



For the unweighted networks, connections between locations, or network ties, will be defined by whether at least one person has moved from one location to the other during the 2007-2013 time period in Somalia. This movement produces a directed tie between those locations. There are three weighted displacement networks, specifically 25th Percentile, 50th Percentile, and 75th Percentile displacement networks. Each displacement network requires a progressively higher threshold to constitute the formation of a tie. This threshold increases to at least 324 people for the 25th Percentile displacement network, at least 835 people for the 50th Percentile displacement network, and at least 2622 people for the 75th Percentile displacement network. Varying threshold levels provides the opportunity to assess whether expected relationships hold across all displacement flow magnitudes. It also accounts for the reality that displacement flows of 10 people between two locations are very different from flows of 1,000 people.

There are two within-network configurations of particular interest for this analysis: preferential attachment and transitivity. Preferential attachment means that certain nodes are more likely to receive ties (Wasserman and Faust, 1994). This configuration in a network would indicate convergence towards specific locations, making preferential attachment a valid proxy for herd cascades. Transitivity means that civilians fleeing location A are divided between locations B and C with movements A→ B and A→C. Then, civilians in location B reconstitute their community by joining their fellow community members in location C with a movement B→C, as is displayed in Figure 1 (Wasserman and Faust, 1994; Papachristos et al., 2013). If transitivity is driving convergence in displacement destinations, then there is evidence that civilians select displacement destinations based on which destination best facilitates the reconstituting of their communities. Rather than following the actions of any member of their society, civilians follow the actions of their own community members. This configuration is thereby a valid proxy for community cascades.

Ethnic homophily can then serve as a measure for co-ethnic cascades. Homophily refers to the expectation that actors with similar characteristics are more likely to form connections with each other (McPherson et al., 2001). In particular, co-ethnic locations are likely to be desirable displacement destinations. This is because as displacement divides origin communities, civilians are likely to look to co-ethnics to help create a new, trustworthy community (Steinberg, 2015; Zilberg, 2011; Whitehouse, 2012; Horst, 2006). Ultimately, homophily exists because people trust and interact with those who are similar to them more than those who are dissimilar to them. Co-ethnics provide durable ties that are valuable during times of instability, including displacement (Habyarimana et al., 2007). The incentive to draw upon the durable ties of co-ethnics increases as displacement flow magnitudes increase. Large displacement flows indicate that there is extreme chaos, thereby increasing the desire to find co-ethnics.

VI. Data on Network Ties

The UNHCR Population Movement Tracking (PMT) initiative provides the displacement data for this analysis. This data tracks internal displacement in Somalia from 2007-2013 on a daily basis through coordination with 48 NGOs in Somalia and the UNHCR office in Nairobi. Internal displacement origins, destinations, dates, and primary reason for displacement are all included in this data source. The data tracks displacement movements, so it is not useful for counting the total number of IDPs. Instead, it is a valuable tool for understanding when people move, where they move to and from, and why they move.

For each displacement movement, the data records one reason for the movement. Rather than dismissing the possibility that multiple factors may motivate displacement, the data simply focuses on the primary reason for each displacement movement. These reasons include insecurity, clan conflict, drought, flood, famine, fire, lack of livelihood, eviction, relocation, IDP return, and forced return (UNHCR, 2007). Insecurity accounts for the overwhelming majority of Somali internal displacement.

However, this data source is not perfect. International NGOs have a very limited presence in Somalia, which minimizes the oversight for local NGOs. In addition, it is very difficult to track all displacement movements. Large movements may overwhelm those attempting to monitor them (Crisp, 1999). Within-city displacement is often missed by monitors (Karen Jacobsen and IDMC, 2008). Civilians moving to stay with family members or friends may not always be counted as displacement. Displacement in rural areas is also difficult to monitor due to the lack of people and infrastructure (Brookings, 2013). Moreover, there are incentives to inflate estimates of internal displacement flows (Watch, 2013).

Despite these concerns, UNHCR's PMT initiative is the first and only publicly available data source that captures internal displacement with such detail. UNHCR has invested substantial resources in collaborating with so many local NGOs, and they are surely able to capture the important displacement trends in Somalia (Lindley 2010b; Schon 2015).

VII. Data on Network Node Attributes

Network nodes were created with four attributes. These attributes include clan, urban, road, and control changes. The clan attribute refers to the largest clan in each location. There is disagreement on the number and structure of clan groups in Somalia, but this paper uses Hawiye, Darod, Dir, Rahanweyn, and Bantu (Lewis, 1994). Urban refers to whether the location is one of

Somalia's district capitals.[4] Road refers to whether the location is within 10 kilometers of a road used by the World Food Program (WFP) on its aid distribution routes. WFP roads are a subset of all roads in Somalia, but it is reasonable to expect that they are the largest and most salient roads in Somalia. Major roads provide opportunities for access to transportation, information, and necessary resources (Joireman et al., 2012; Klaeger, 2013). The control changes attribute measures whether there have been any battles where territorial control changed hands within 10 kilometers of a given location. This attribute approximates the level of competition for each location. All of these attributes are displayed on a map in the appendix.

The urban attribute is a dichotomous variable. It is coded as 1 when the location is a district capital and 0 otherwise. Some district capitals in Somalia contain small populations, so they are not all equally important. Still, district capitals are most likely to be the locations where civilians can find humanitarian aid, jobs, and other resources when they are in need. Out of 296 locations, 65 of them are urban.

Road is also a dichotomous variable. It is coded as 1 when the location is within 10 kilometers of a road used by the WFP and 0 otherwise. Locations close to roads are likely to be easier to leave and easier to reach. They are also more likely to have access to humanitarian assistance. There are 170 locations near WFP roads. From these 170 locations, 120 of them are not near urban areas. On the other hand, 15 urban areas are not near WFP roads.

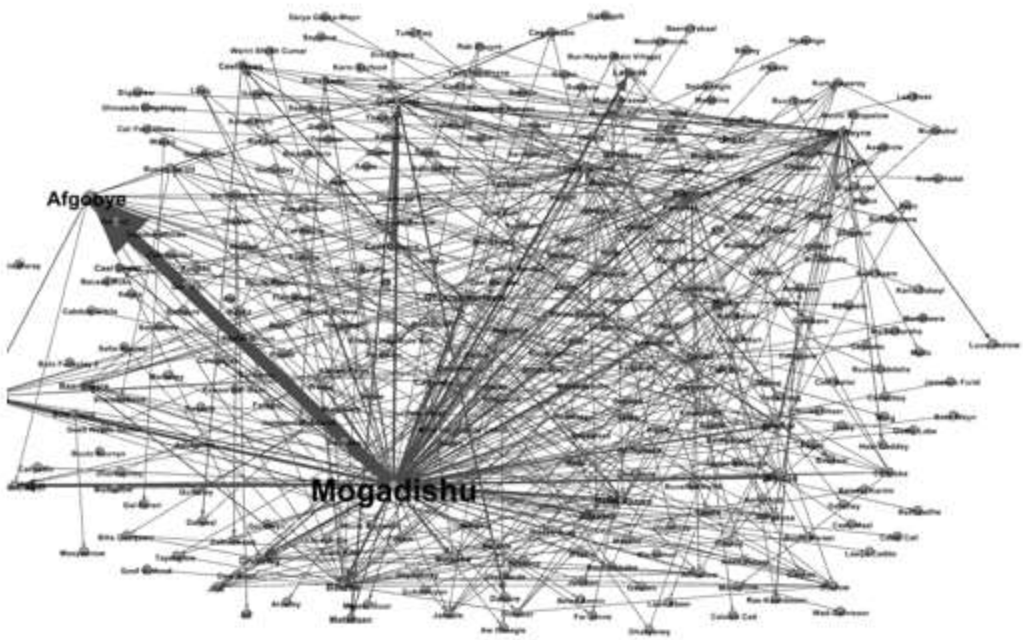
Clan is a factor variable. It codes each node based on the largest clan in each location. While the proper manner in which to disaggregate the Somali population into clans is an open debate, this paper uses Hawiye, Darod, Dir, Rahanweyn, and Bantu. In order to code each location, a map image of the distribution of clans in Somalia was georeferenced using 8 reference points. Locations within a clan zone are coded as being populated by that clan. This variable does not capture the distribution of clans within each location, so it is unable to distinguish whether there is a neighborhood within a location that is heavily populated by a minority clan. However, it is able to provide information about the main clan in each location. Out of the 296 locations, 3 are Bantu, 65 are Darod, 22 are Dir, 159 are Hawiye, and 47 are Rahanweyn.

This coding neglects the distribution of clans in each location, as well as whether there are prominent neighborhoods of minority clans in a given location. Research on Somali refugees often notes how they cluster with their clans and sub-clans within cities, such as Nairobi and Johannesburg (Thompson, 2015; Horst, 2006; Ndzovu, 2014). Future research could make a valuable contribution by providing more fine-grained data on the distributions of clans within Somalia.

The control changes attribute is another dichotomous variable. It is coded as 1 when there was at least one battle involving a change in territorial control from 2007-2013 within 10 kilometers of the location and 0 otherwise (Clionadh Raleigh et al., 2010). This variable is more

[4] This study does not use population data due to the unreliability of population data in Somalia. Population estimates that exist can vary dramatically between sources. See the variation between Lindley (2010) and 2006 UNDP data for an example.

Figure 2. Somalia Displacement Flow Network*



*Label size is based on weighted in-degree centrality. Edges are weighted based on IDP flows.

appropriate than a count of violent events because it can show whether one armed group was firmly in control of a location. Unstable territorial control could increase the likelihood of displacement from locations and decrease the desirability of a location as a displacement destination. There are 64 locations with at least one control change.

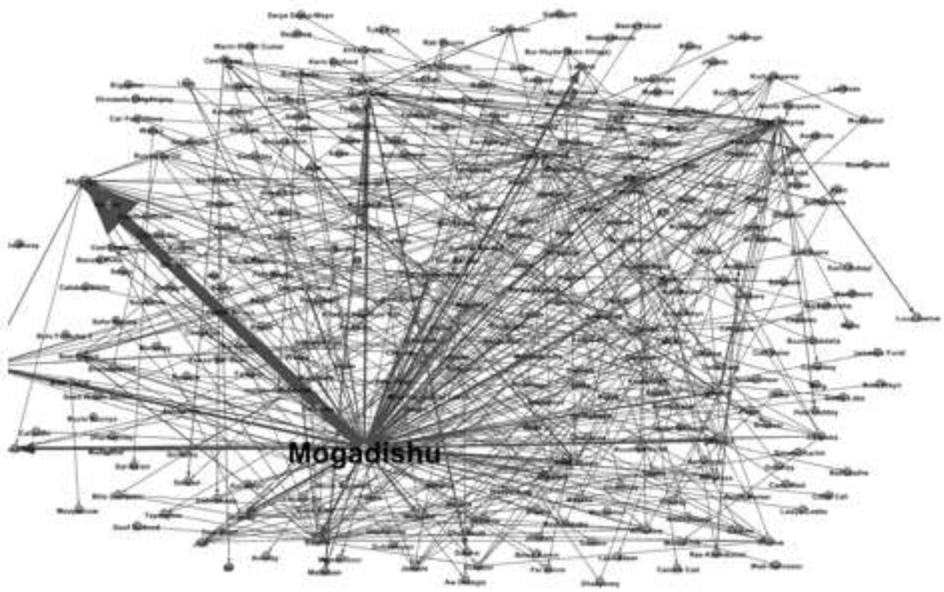
Variables involving these node attributes, as well as configurations of network ties, reveal a great deal of information about displacement patterns. While ERGMs are needed to properly assess the role of cascades, descriptive information about the network can provide important context and information about the kinds of factors that may be motivating displacement cascades.

VIII. Descriptive Information about Internal Displacement in Somalia

In order to illustrate the displacement flow network in Somalia from 2007-2013, there are six plots of the internal displacement network. All of these plots display the magnitude of the displacement flow between locations by varying line thickness. Thicker lines indicate larger displacement flow magnitudes. All nodes are represented by dots, and the location name labels each node. The label size represents the weighted in-degree in Figure 2 and weighted out-degree in Figure 3. Additional figures that are displayed in color in the online appendix use label size to represent the weighted degree of each location. These figures represent node and edge colors based on attribute characteristics.

These plots indicate that there are some locations with particularly notable displacement activity. Mogadishu is clearly the key city. As Somalia’s capital and largest city, this is

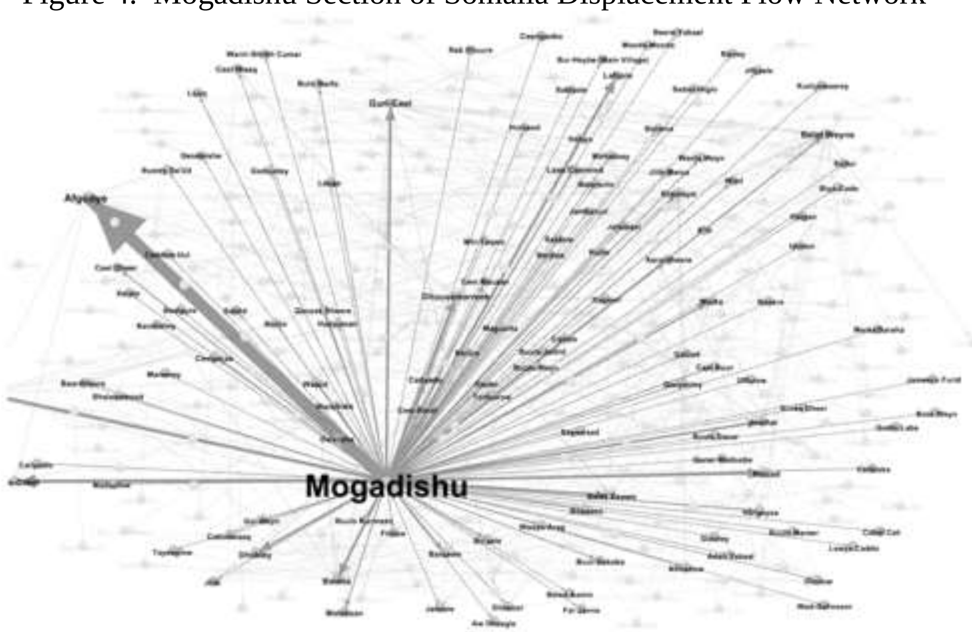
Figure 3. Somalia Displacement Flow Network*



* Label size is based on weighted out-degree centrality. Edges are weighted based on IDP flows.

understandable. Mogadishu is a hotly contested city by Somalia's armed groups, territorial control changes frequently, and humanitarian aid organizations cluster in Mogadishu and its airport. With large displacement magnitudes to and from Mogadishu, it would be worthwhile to unpack the numerous factors at play within the city. While this in-depth analysis is beyond the scope of this paper, Figure 4 shows only the displacement flows to and from Mogadishu for descriptive benefit.

Figure 4. Mogadishu Section of Somalia Displacement Flow Network*



*Label size is based on weighted degree centrality. Edges are weighted based on IDP flows.

Table 1. Weighted Degree Centrality Measures

	Weighted Degree	Weighted In-Degree	Weighted Out-Degree
#1	Mogadishu (1115853)	Afgooye (255709)	Mogadishu (1063203)
#2	Afgooye (311639)	Gaalkacyo (66879)	Guri-Ceel (157391)
#3	Guri-Ceel (199090)	Xaawo-Cabdi (61631)	Belet Weyne (95047)
#4	Belet Weyne (118231)	Dhobley (59326)	Afgooye (55930)
#5	Gaalkacyo (89804)	Mogadishu (52650)	Laas Caanood (53759)

To highlight important locations beyond Mogadishu, I turn to weighted in-degree and out-degree centrality measures in Table 1. These measures indicate which locations receive and send the most displaced civilians respectively. While Mogadishu is by far the most common displacement origin and destination location, Afgooye and Dhuusamarreeb are also common origin and destination locations. Guri-Ceel and Belet Weyne are common origin locations, whereas Gaalkacyo and Dhobley are common destination locations. Afgooye is the second most important city in this network. Much of the displacement to and from Afgooye involves Mogadishu, highlighting that the Mogadishu-Afgooye dyad is also the most important dyad for displacement. Afgooye is a common first destination for civilians fleeing Mogadishu. In addition, civilians often travel through Afgooye on the way to Mogadishu. These centrality measures indicate that displaced Somali civilians do converge on specific locations.

Displacement behavior also varies by clan as Table 2 displays. The Hawiye and Darod are the two largest clans, so, understandably, their locations have the largest in-flows and out-flows. On average, Hawiye locations send and receive the largest amounts of displaced people. Darod locations also send and receive large numbers of displaced persons, albeit less than Hawiye locations. Rahanweyn and Dir locations receive far more displaced people than they send, on average. Bantu locations, due to some extent by the relatively small Bantu population in Somalia, do not send nor receive large numbers of displaced people.

Table 2. Displacement by Clan

	Average Displacement In-Flow	Average Displacement Out-Flow
Bantu	609	0
Darod	5486	4801
Dir	7407	3723
Hawiye	8993	11647
Rahanweyn	7289	1030

.

Table 3. Displacement Out-Flow by Attribute Traits

	Urban	**Road**	**Control Changes**	**ALL ATTRIBUTES**
Urban	11,880	156,866	42	
Road	156,866	1,821,790	7,672	
Control Changes	42	7,672	4,886	
ALL ATTRIBUTES				90,105

Table 4. Displacement In-Flow by Attribute Traits

	Urban	**Road**	**Control Changes**	**ALL ATTRIBUTES**
Urban	28,459	311,491	8,063	
Road	311,491	1,066,419	44,814	
Control Changes	8,063	44,814	59,389	
ALL ATTRIBUTES				380,013

There are also important dynamics to note with the urban, road, and control changes attributes as shown in Table 3. Tables of total displacement flows to and from locations highlight important trends. Locations along roads send the most displaced people, followed by urban locations, and then locations with control changes. This shows that transportation options facilitate displacement. Urban locations with control changes and no major roads send almost no displaced people. This reveals just how vital roads are for displacement. It also shows that locations with changes in territorial control deter displacement.

There are additional observations to make regarding the characteristics of locations receiving displaced people as shown in Table 4. Again, locations with roads receive the most displaced people, followed by urban locations and then locations with control changes. Also, urban locations with control changes and without roads receive the fewest displaced people. It also adds to the argument that roads facilitate displacement. Also, urban areas receive far more displaced people than they send.

It is also clear that displacement tends to occur in specific directions. While there are 507 edges in the unweighted network, only 37 dyads had reciprocal ties. When the threshold for a tie is set at the 25th percentile, 28 dyads have reciprocal ties out of 363 edges. At the 50th percentile, 17 dyads have reciprocal ties out of 239 edges. At the 75th percentile, 6 dyads have reciprocal ties out of 123 edges. So, when civilians move between two locations during displacement, they tend to move in one direction. Reciprocity is very uncommon.

Table 5. Network Node Summary Statistics

	Unweighted	25 Percentile	50 Percentile	75 Percentile
Bantu	3	3	1	0
Dir	22	14	10	7
Rahanweyn	47	27	15	9
Darod	65	50	37	19
Hawiye	159	127	95	64
Urban	65	58	53	43
Control Changes	64	54	46	32
Road	170	131	99	67
Total	296	221	158	99

IX. Consideration of Sparse Networks

The unweighted network is a very sparse network, with a density of 0.006. This means that only 0.6% of possible ties between nodes are realized. As thresholds are adjusted to the 25th, 50th, and 75th percentiles, many nodes become isolates, and the density decreases to even smaller levels. This creates problems with convergence for the ERGM models. ERGM models are already known to be unstable models that can have challenges with model degeneracy, so this is a practical concern that must be overcome (Wasserman and Faust, 1994). To overcome this obstacle, I disregard isolates from all weighted network models.

Nodes that are disregarded at each threshold no longer have a sufficient displacement flow either to or from the location to have any ties to other nodes. Based on Table 5, the locations with control changes and Rahanweyn clan members are disregarded at the fastest rate due to the small displacement flows to or from them.

The small displacement flows to and from locations with Rahanweyn clan members offers an interesting observation about conflict dynamics in Somalia. While many clans and sub-clans fight each other in Somalia, some tensions are more serious than others. Darod and Hawiye clan tensions are arguably the most important clan tensions in south and central Somalia (Kapteijns, 2013). Also, as the map in the Appendix illustrates, Rahanweyn clans are not the largest group in many major Somali cities like Mogadishu or Kismayo. Thus, while there are many Rahanweyn locations with displacement, the magnitude of Rahanweyn displacement appears smaller than the magnitude of displacement to and from locations inhabited by other clans.

X. ERGM Results

With this understanding of the descriptive characteristics of the Somali displacement network, we can proceed to the ERGMs. The ERGMs yield the opportunity for rigorous analysis

Table 6. Unweighted Directed Network

	Estimate	SE	Estimate	SE	Estimate	SE
Edges	-5.678***	0.1112	**-6.333*** **	**0.4820**	-5.603***	0.1195
Main Effects						
In-Degree Urban	-0.322*	0.1235	**-0.033**	**0.0639**	-0.291*	0.1227
Out-Degree Urban	-0.440	0.1260	**-0.191**	**0.1038**	-0.444***	0.1280
In-Degree Control Changes	-0.059	0.1152	**0.161***	**0.0802**	-0.062	0.1111
Out-Degree Control Changes	-0.452	0.1244	**-0.242***	**0.0951**	-0.452***	0.1241
In-Degree Road	0.350*	0.0991	**-0.040**	**0.0581**	0.320*	0.0983
Out-Degree Road	0.759	0.1029	**0.349*** **	**0.0573**	0.758***	0.1025
Homophily						
Clan	0.100*	0.0933	**0.016**	**0.0597**	0.101	0.0928
Network Structure						
Transitivity			**2.616*** **	**0.4458**		
Preferential Attachment					-0.269	0.1900
AIC	120980		**5519**		5912	
Number of Nodes			296			
Displacement Threshold			1			

of varying cascade types. In this analysis of cascade types, observed trends exist while controlling for the monadic effects of transportation costs, violence, and urban areas.

Goodness of fit tests show that dyad dependence models are the most appropriate at all threshold levels. At the unweighted, 25th, and 50th percentiles, the best model specifications at each threshold level include transitivity and not preferential attachment. At the 75th percentile, the best model specification includes both transitivity and preferential attachment.[5] Model results in the tables below show the Akaike Information Criteria (AIC) statistic for each model. They also show the number of network nodes and the displacement flow threshold required for a tie to exist. Additional goodness of fit results are included in the appendix.

a. How Herd Cascades Influence Internal Displacement Destinations

Model results reveal important nuances in how herd cascades, measured as preferential attachment, influence internal displacement destinations. Table 6 and Table 7 show that herd cascades are not statistically significant for the unweighted network or for the 25th percentile

[5] Models including both the transitivity and preferential attachment terms do not converge with the unweighted and 50th percentile networks. This indicates that these model specifications do not fit the data well.

Table 7. 25th Percentile Directed Network

	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Edges	-5.257***	0.1240	-6.108***	0.2097	**-5.487***	**0.1285**	-5.223***	0.1375
Main Effects								
In-Degree Urban	0.089	0.1340	0.201***	0.0407	**0.199**	**0.1389**	0.0865	0.1328
Out-Degree Urban	-0.268	0.1468	-0.313***	0.0391	**-0.056**	**0.1329**	-0.2674	0.1496
In-Degree Control Changes	-0.093	0.1377	-0.048	0.0391	**0.127**	**0.1080**	-0.0913	0.1323
Out-Degree Control Changes	-0.527***	0.1536	-0.527***	0.0481	**-0.243**	**0.1564**	-0.528***	0.1533
In-Degree Road	0.157	0.1184	0.037	0.0288	**-0.056**	**0.1211**	0.1499	0.1154
Out-Degree Road	0.427***	0.1177	0.335***	0.0364	**0.120**	**0.0844**	0.429***	0.1185
Homophily								
Clan	0.275*	0.1102	0.278***	0.0305	**0.149**	**0.1208**	0.272*	0.1084
Network Structure								
Transitivity			2.952***	0.1792	**1.819***	**0.0646**		
Preferential Attachment			0.845	1857.1505			-0.1192	0.2166
AIC	63357		3833		**3761**		4048	
Number of Nodes				221				
Displacement Threshold				324				

network. Instead, Table 8 and Table 9 show that herd cascades are statistically significant at the 50^{th} and 75^{th} percentile. In short, herd cascades matter only at high displacement levels.

a. How Co-ethnic Cascades Influence Internal Displacement Destinations

Co-ethnic cascades follow a similar pattern as herd cascades, except they begin to matter at lower displacement levels. Table 6 shows that co-ethnic cascades did not occur for the

Table 8. 50th Percentile Directed Network

	Estimate	SE	Estimate	SE	Estimate	SE
Edges	-5.782***	0.1796	**-5.290*****	**0.1335**	-6.029***	0.2074
Main Effects						
In-Degree Urban	0.232	0.1612	**-0.157**	**0.0885**	0.290	0.1830
Out-Degree Urban	0.948***	0.1450	**0.340*****	**0.0866**	0.951***	0.1464
In-Degree Control Changes	0.115	0.1642	**-0.241****	**0.0863**	0.151	0.1824
Out-Degree Control Changes	1.138***	0.1496	**0.430*****	**0.0663**	1.139***	0.1510
In-Degree Road	0.088	0.1518	**0.021**	**0.0813**	0.111	0.1735
Out-Degree Road	-0.051	0.1683	**0.003**	**0.0591**	-0.054	0.1690
Homophily						
Clan	0.473***	0.1367	**0.167****	**0.0631**	0.489***	0.1362
Network Structure						
Transitivity			**1.901*****	**0.1152**		
Preferential Attachment					0.733**	0.2764
AIC	34255		**2296**		2387	
Number of Nodes			158			
Displacement Threshold			835			

unweighted network. Table 7 shows that when the percentile is set at the 25th percentile, three out of the four models yield a significant coefficient for co-ethnic homophily. This provides strong evidence that co-ethnic cascades begin at the 25th percentile. Then, Table 8 and Table 9 show that co-ethnic homophily is significant across all models for thresholds at the 50th percentile and at the 75th percentile. Therefore, while co-ethnic cascades do not matter at low displacement levels, they become important at lower levels than herd cascades. This supports the view that civilians seek out people with similar characteristics when possible, rather than simply 'following the crowd' as herd cascades would suggest.

a. How Community Cascades Influence Internal Displacement Destinations

Meanwhile, community cascades influence internal displacement destinations at all thresholds of displacement magnitudes. Tables 6-9 show that transitivity is significant across all models. Regardless of whether displacement levels are high or low, civilians follow their origin community members.

This discrepancy between the results for community cascades versus the results for herd cascades and co-ethnic cascades support the assertion that displacement cascades function differently depending upon whether they are following personal connections. Herd cascades involve people 'following the crowd'. Co-ethnic cascades involve people following others with similar characteristics. Community cascades involve people following specific people from their

Table 9. 75th Percentile Directed Network

	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Edges	-5.738***	0.3220	**-6.857*** **	**0.4232**	-5.726***	0.3049	-6.517***	0.4109
Main Effects								
In-Degree Urban	-0.053	0.2234	**-0.011**	**0.3143**	0.051	0.2094	-0.134	0.3086
Out-Degree Urban	-0.882**	0.2742	**-0.715** **	**0.2639**	-0.722**	0.2639	-0.876**	0.2773
In-Degree Control Changes	0.018	0.2228	**0.240**	**0.2955**	0.127	0.2008	0.067	0.3094
Out-Degree Control Changes	-1.012***	0.2675	**-0.824** **	**0.2537**	-0.860***	0.2571	-1.005***	0.2702
In-Degree Road	0.240	0.2151	**0.189**	**0.3122**	0.043	0.2053	0.413	0.3080
Out-Degree Road	1.723***	0.2820	**1.457*** **	**0.2764**	1.481***	0.2875	1.719***	0.2839
Homophily								
Clan	0.503**	0.1921	**0.434***	**0.1810**	0.399*	0.1661	0.552**	0.2022
Network Structure								
Transitivity			**2.099*** **	**0.1924**	1.507***	0.1496		
Preferential Attachment			**2.393*** **	**0.4084**			1.774***	0.3853
AIC	13392		**1114**		1152		1160	
Number of Nodes				99				
Displacement Threshold				2622				

personal networks. This distinction reveals a critical hierarchy governing the importance of each cascade type, in which civilians prioritize their social networks, then groups with similar characteristics, and then general crowds. Thus, rather than classifying cascades as a single category of behavior, it really is important to disaggregate displacement cascades into multiple typologies.

Jonny Steinberg describes this hierarchy in practice in his biographical account *A Man of Good Hope*. This account tells the story of a Somali man's displacement from Mogadishu as a child in 1991, life in Kenya and Ethiopia, moving down to South Africa, and then life in South Africa. Every time Somalis reach a new and unfamiliar place, their first response is to inquire about the whereabouts of other Somalis. This process begins with a search for close family members. If they cannot be found, then people move to more and more distant sub-clan or clan ties.

Within sub-clans and clans, Somalis are noted for their generosity, but this generosity is unreliable across clan lines (Menkhaus, 2003; Lewis, 1994). This dynamic makes the distinction between herd cascades, co-ethnic cascades, and community cascades particularly critical in the Somali context. However, Somalia is far from the only country with ethnic divisions. Especially during the polarizing conditions of armed conflict, distinctions in the patterns of different cascade types are likely to appear in many contexts.

XI. Applications for Future Research

These findings, drawn from the context of Somalia, would be valuable to test in other contexts. Like Somalia, African countries such as Libya, Central African Republic, South Sudan, and the Democratic Republic of the Congo all face the challenges of conflict and large-scale displacement. Their civilians must also deal with challenging ethnic, tribal, or clan politics, and weak states. It is therefore likely that patterns in the formation of herd cascades, co-ethnic cascades, and community cascades would be similar between these cases. If subsequent analyses contradict this expectation, they would have the potential to contribute valuable nuances from the perspective of their own unique contexts.

These cascade models can help explain a variety of other mobilization activities as well. Protest mobilization may involve a combination of herd cascades, community cascades, and co-ethnic cascades. Rebel groups and terrorist organizations also may employ all three of these cascade models. Studying cascade types during other mobilization activities can reveal whether they demonstrate the same kinds of patterns. Cascade models have been a powerful tool for social scientists attempting to explain political mobilization. They will become even more powerful as we disaggregate and develop additional nuance.

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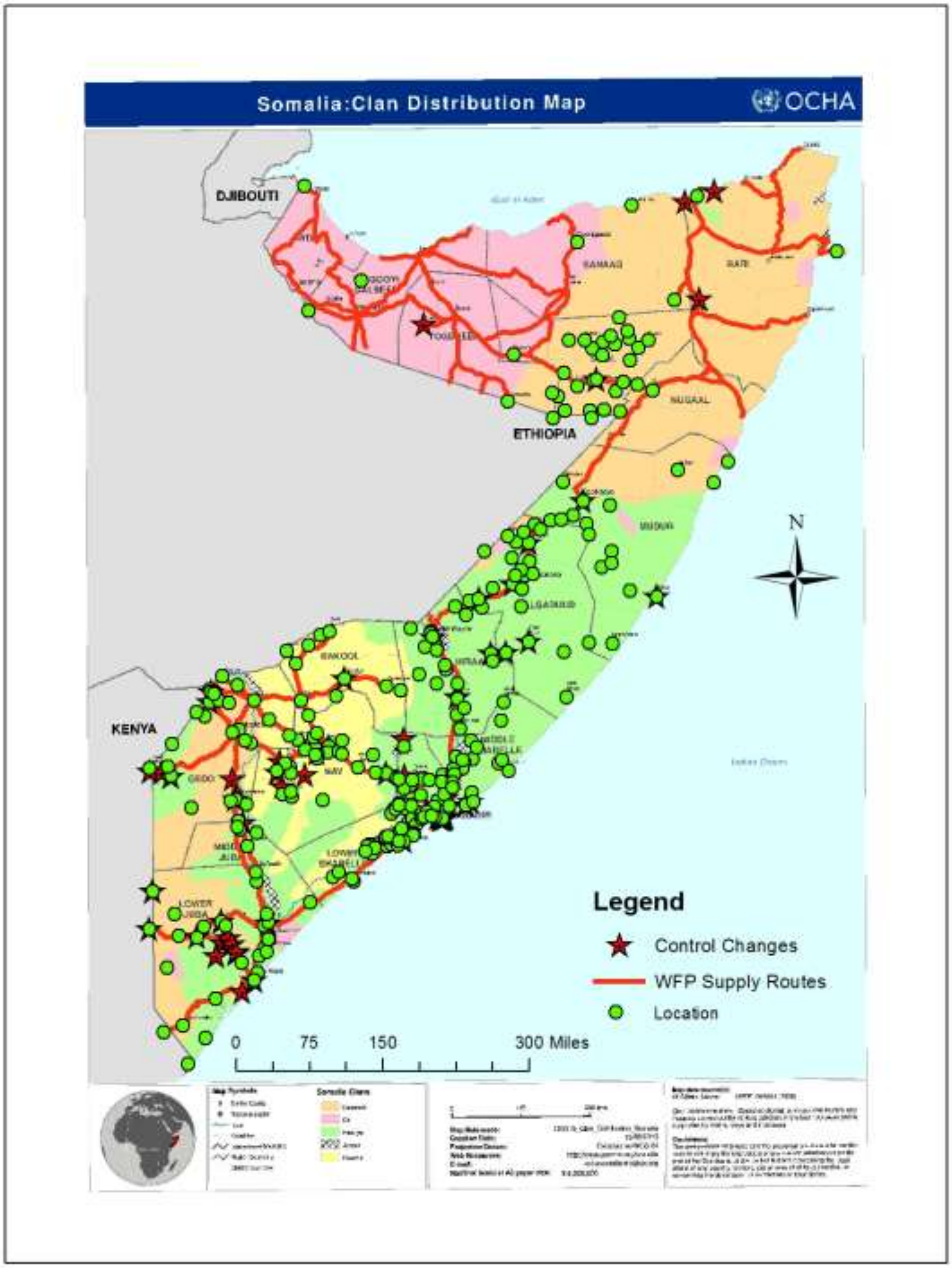
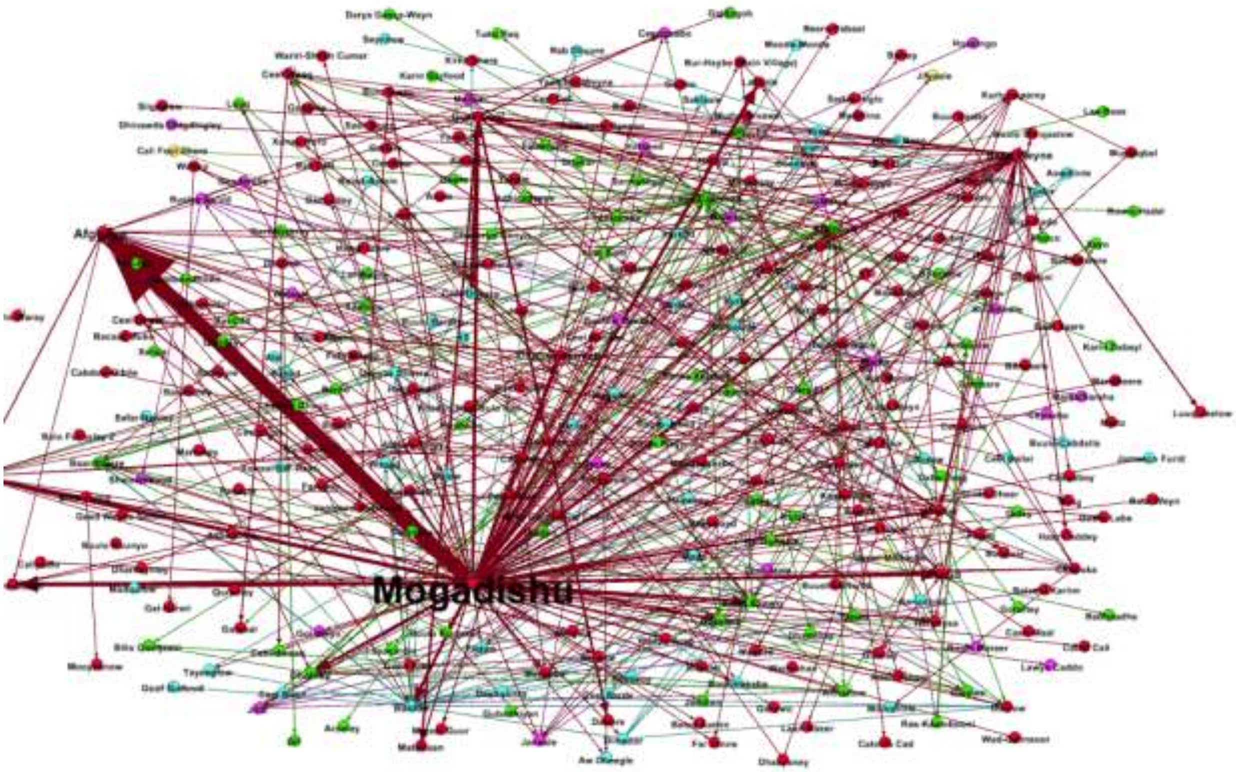
Appendix

Below is the map created in ArcGIS showing the variables used to create the node attributes.



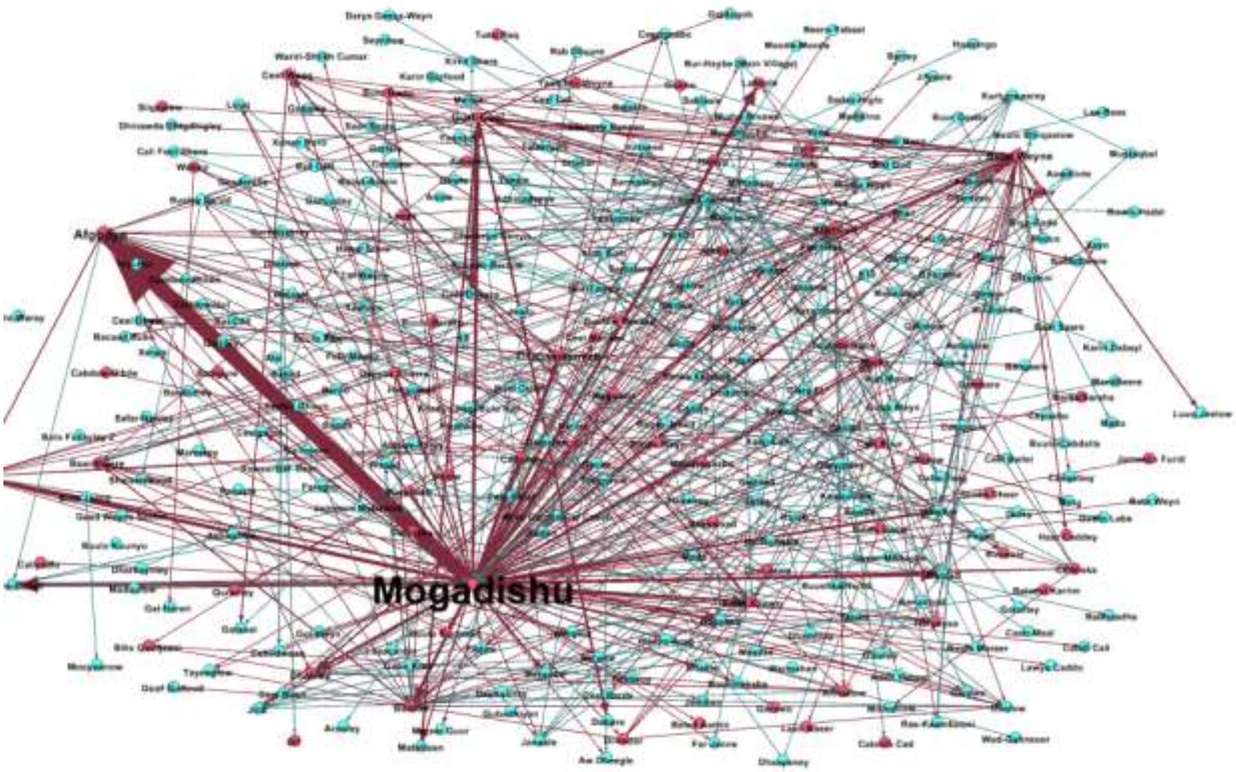
Below are the network plots with colors based on node attributes that are mentioned in the main text.

Somalia Displacement Flow Network by Clan



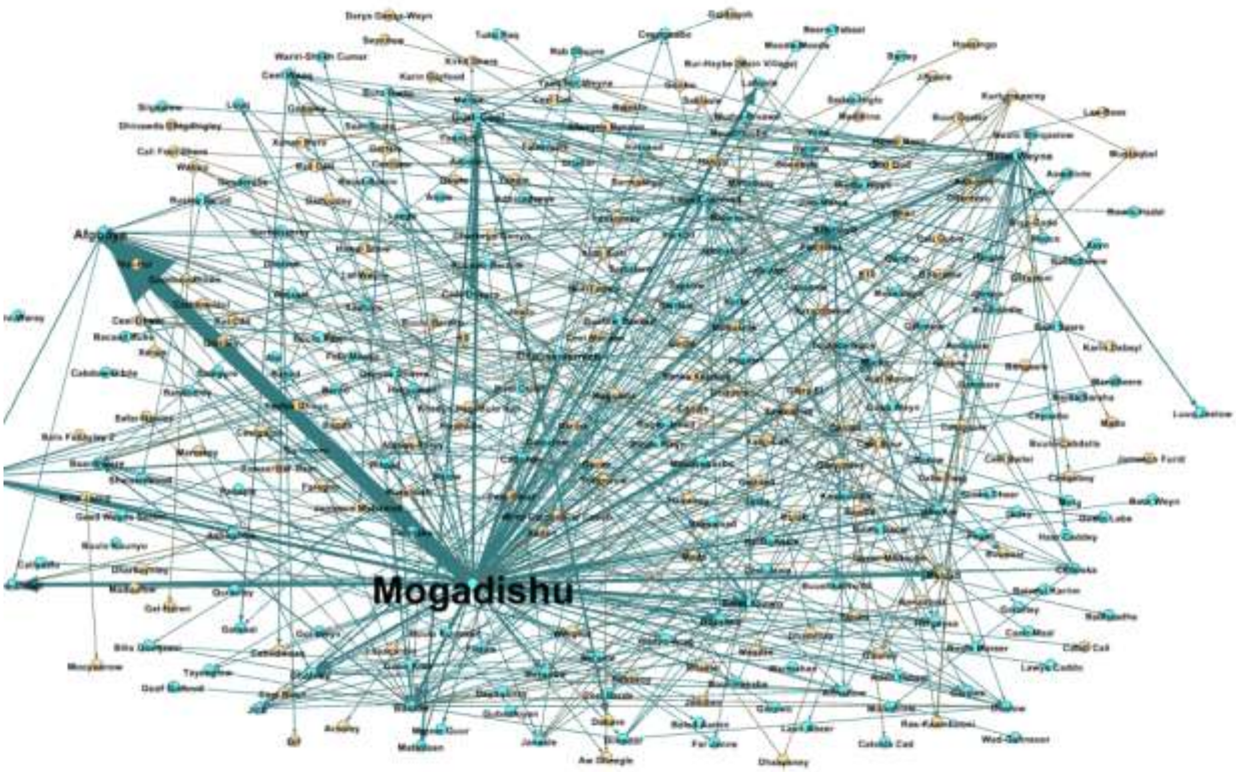
Note: Label size is based on weighted degree centrality. Edges are weighted based on IDP flows. Red nodes are Hawiye. Green nodes are Darod. Purple nodes are Dir. Blue nodes are Rahanweyn. Yellow nodes are Bantu.

Somalia Displacement Flow Network by Control Changes



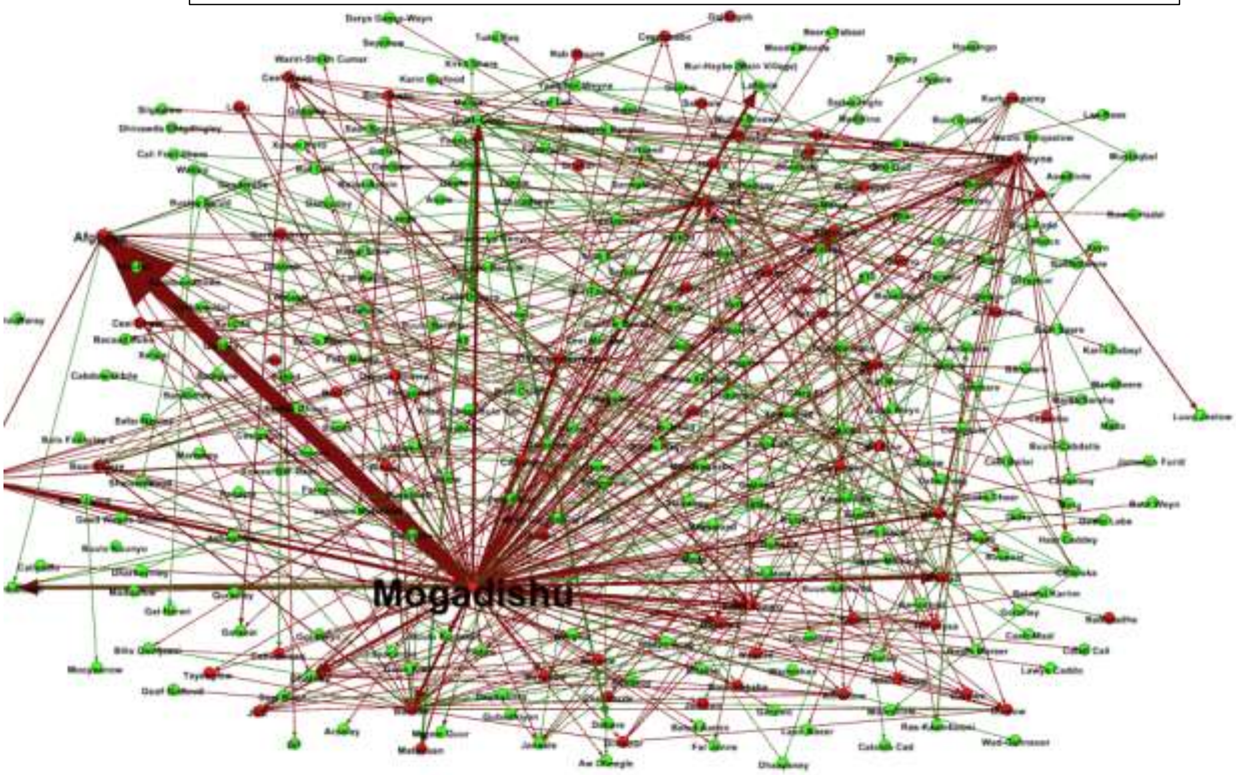
Note: Label size is based on weighted degree centrality. Edges are weighted based on IDP flows. Red nodes have control changes. Blue nodes do not have control changes.

Somalia Displacement Flow Network by Road



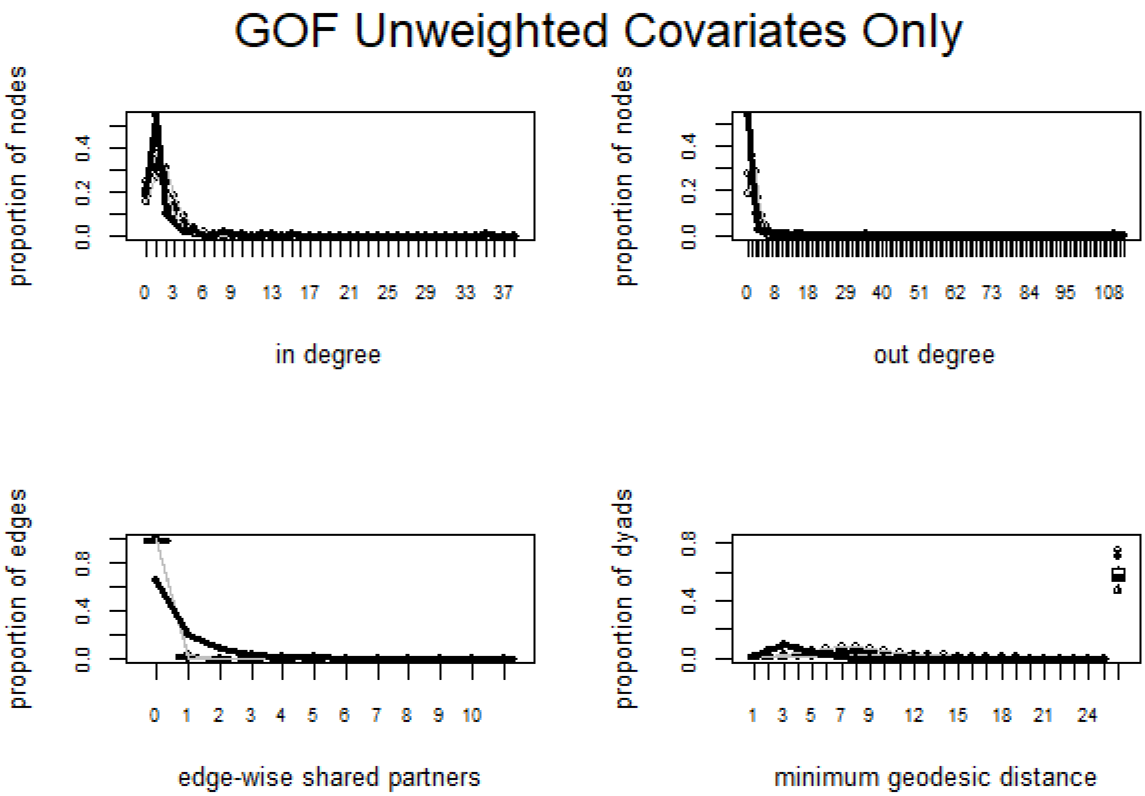
Note: Label size is based on weighted degree centrality. Edges are weighted based on IDP flows. Blue nodes have roads. Orange nodes do not have roads.

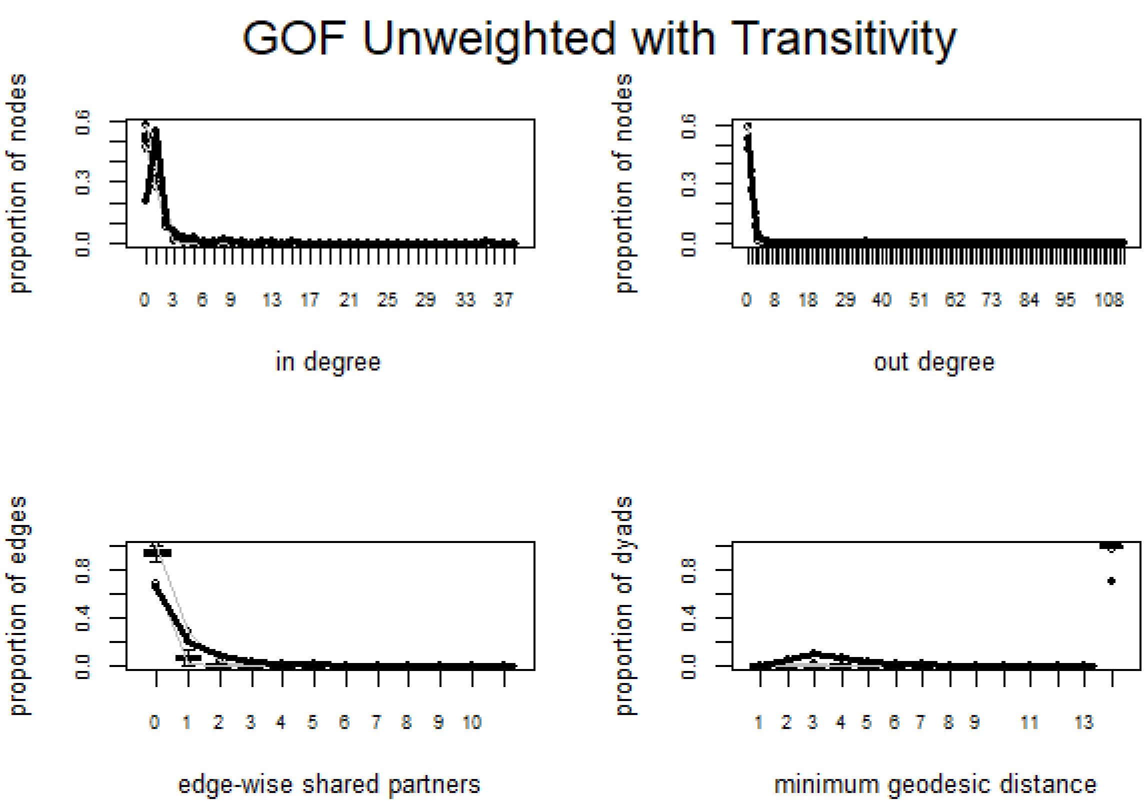
Somalia Displacement Flow Network by Urban



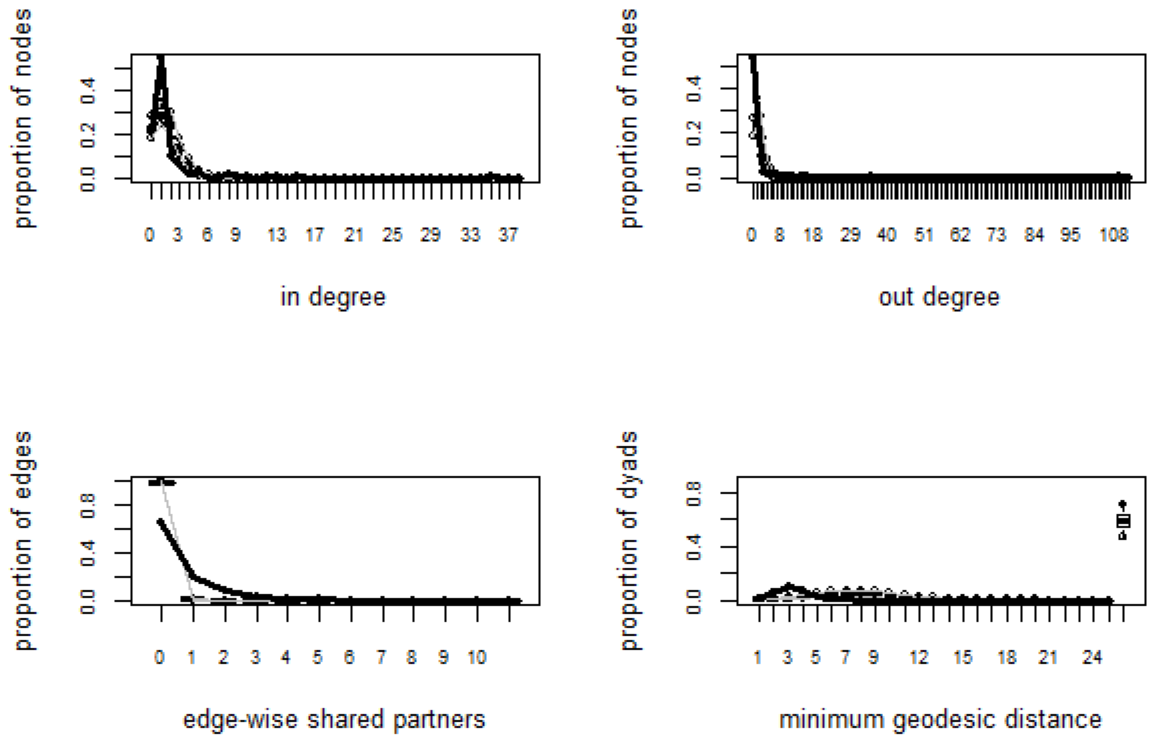
Note: Label size is based on weighted degree centrality. Edges are weighted based on IDP flows. Red nodes are urban. Green nodes are rural.

Below are the goodness of fit plots for each ERGM model. These plots informed the selection of the best fitting models. In the main text, the best fitting model at each threshold level turns out to be the model with the lowest AIC statistic.

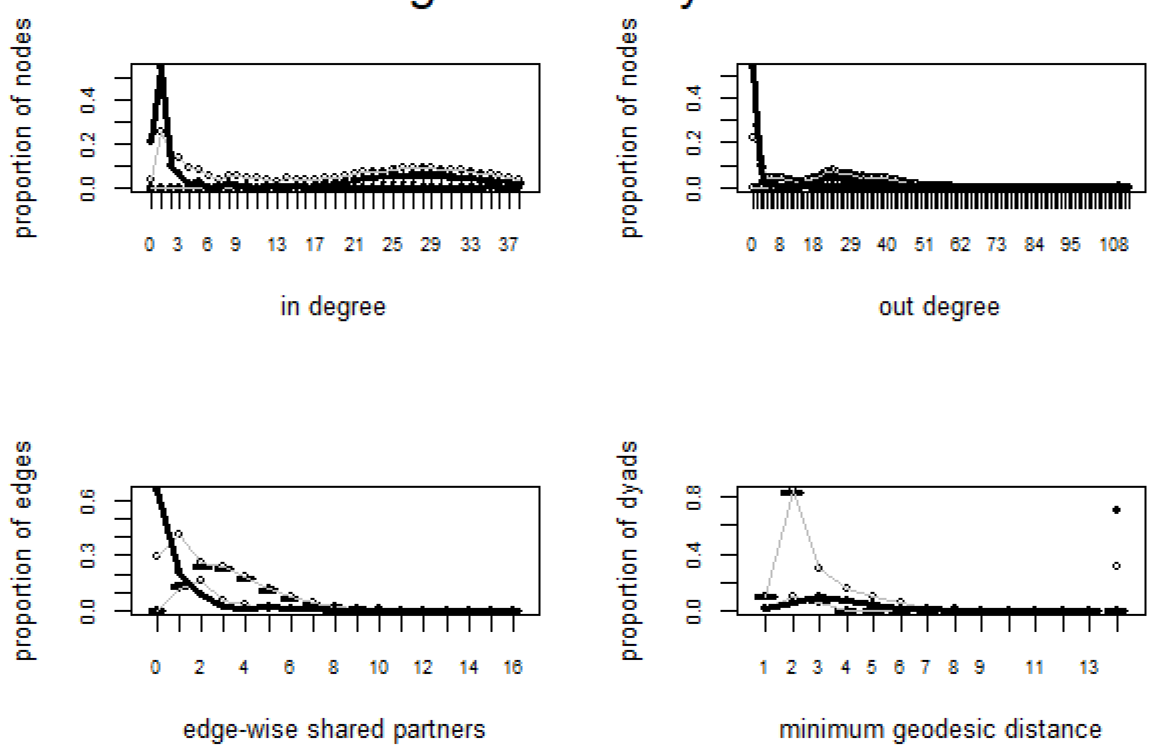

GOF Unweighted Covariates Only
proportion of nodes
0.0 0.2 0.4
0 3 6 9 13 17 21 25 29 33 37
in degree
proportion of nodes
0.0 0.2 0.4
0 8 18 29 40 51 62 73 84 95 108
out degree
proportion of edges
0.0 0.4 0.8
0 1 2 3 4 5 6 7 8 9 10
edge-wise shared partners
proportion of dyads
0.0 0.4 0.8
1 3 5 7 9 12 15 18 21 24
minimum geodesic distance

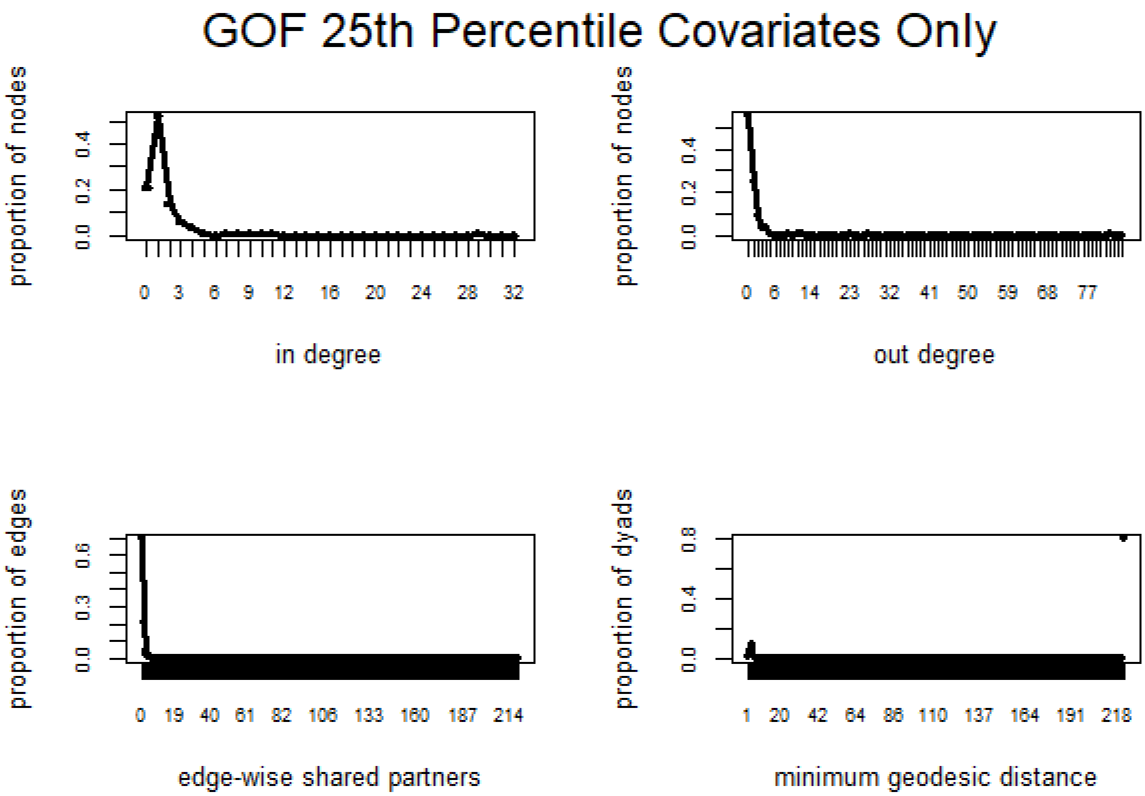

GOF Unweighted with Transitivity
proportion of nodes
0.0 0.3 0.6
0 3 6 9 13 17 21 25 29 33 37
in degree
proportion of nodes
0.0 0.3 0.6
0 8 18 29 40 51 62 73 84 95 108
out degree
proportion of edges
0.0 0.4 0.8
0 1 2 3 4 5 6 7 8 9 10
edge-wise shared partners
proportion of dyads
0.0 0.4 0.8
1 2 3 4 5 6 7 8 9 11 13
minimum geodesic distance

GOF Unweighted with Preferential Attachment



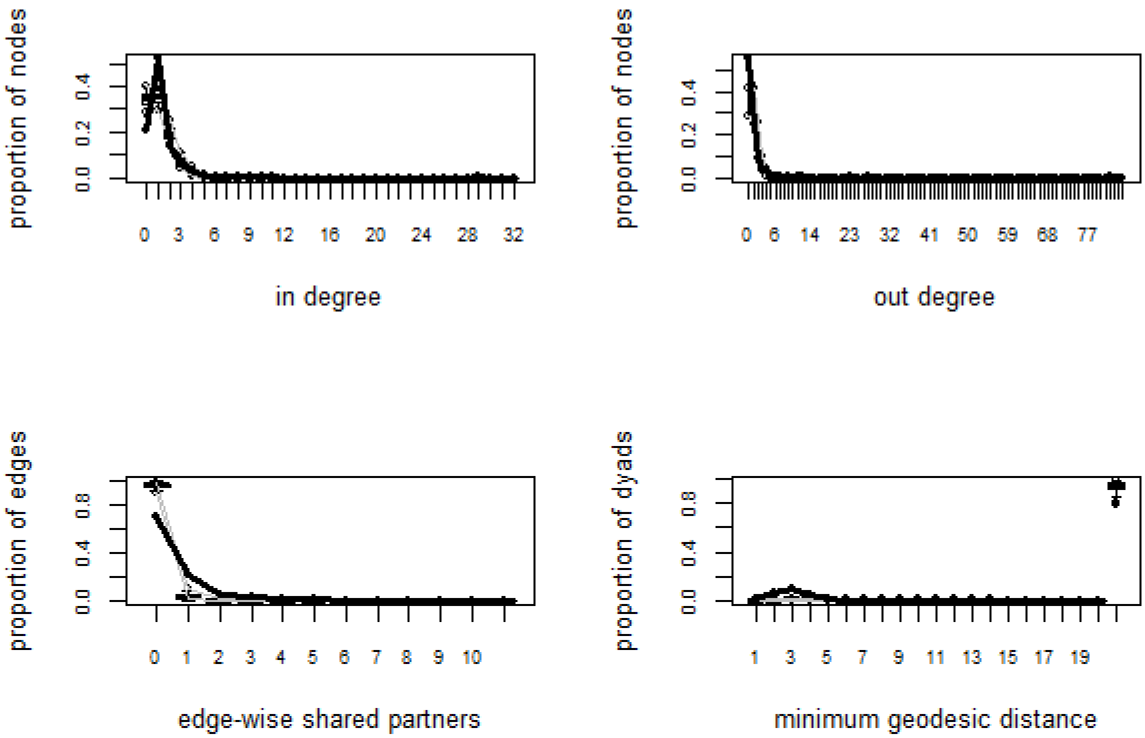
GOF Unweighted with Systemic Variables



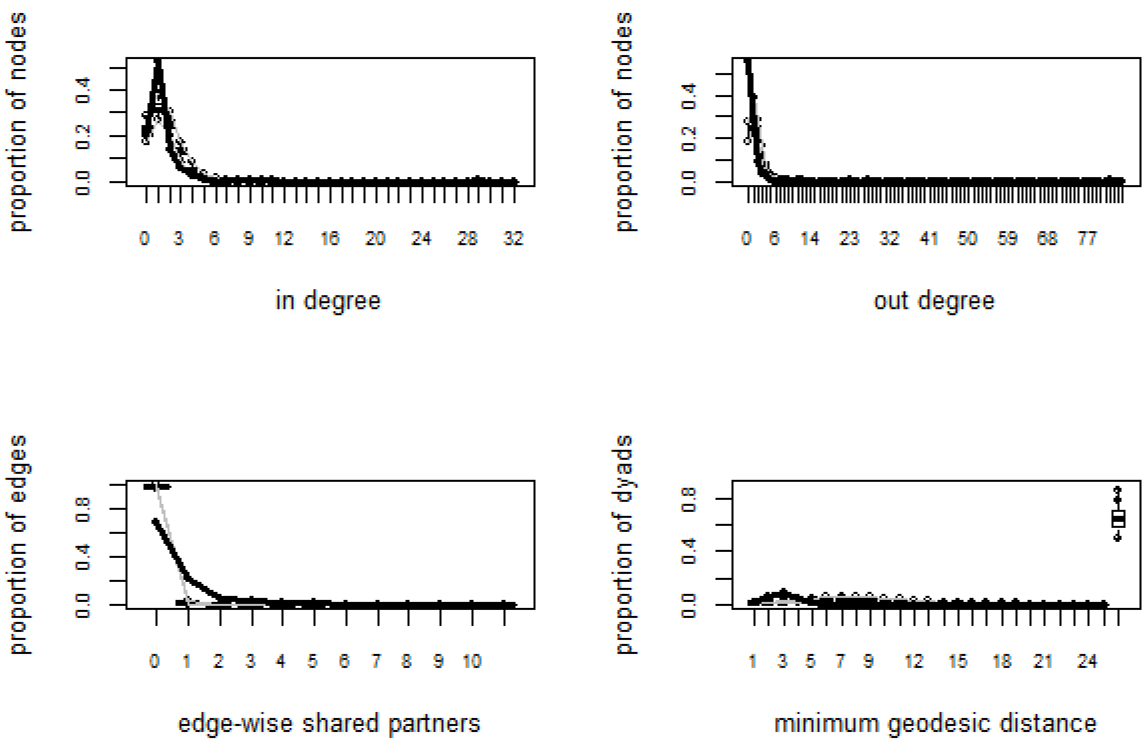


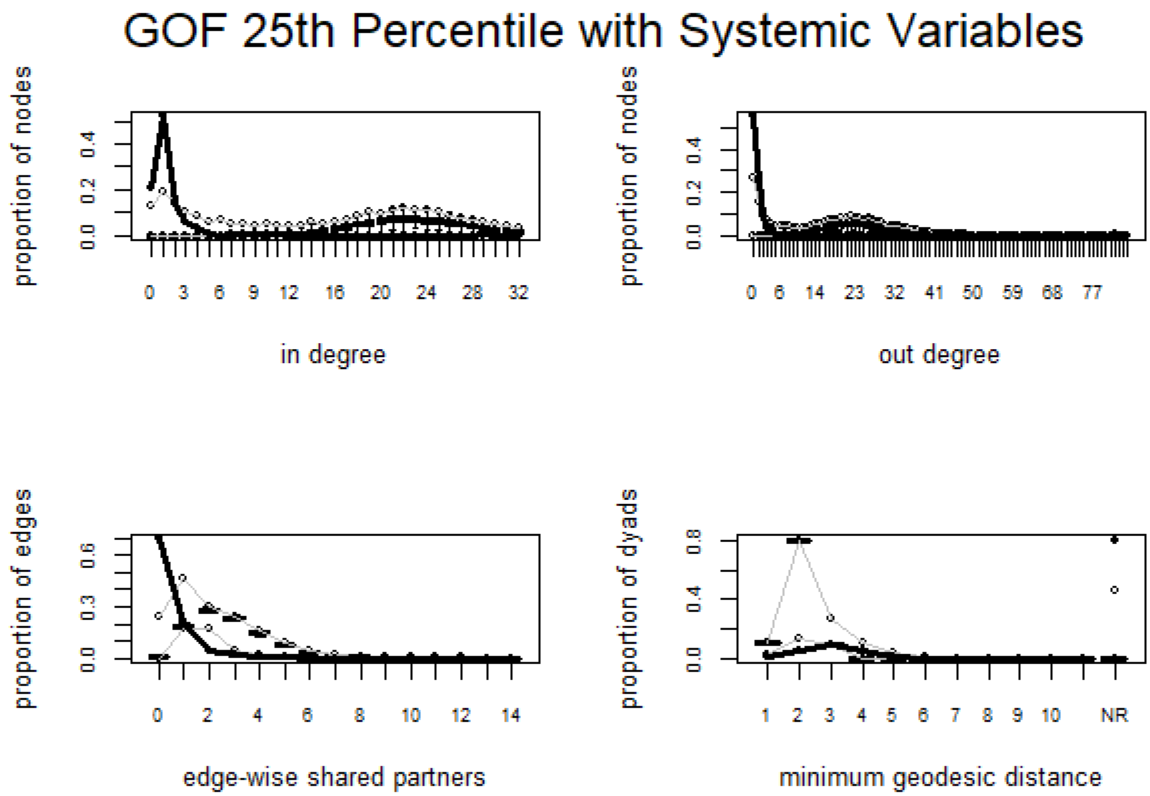
Note: These diagnostics produced some error messages, which is why there are thick solid black lines on two of the plots.

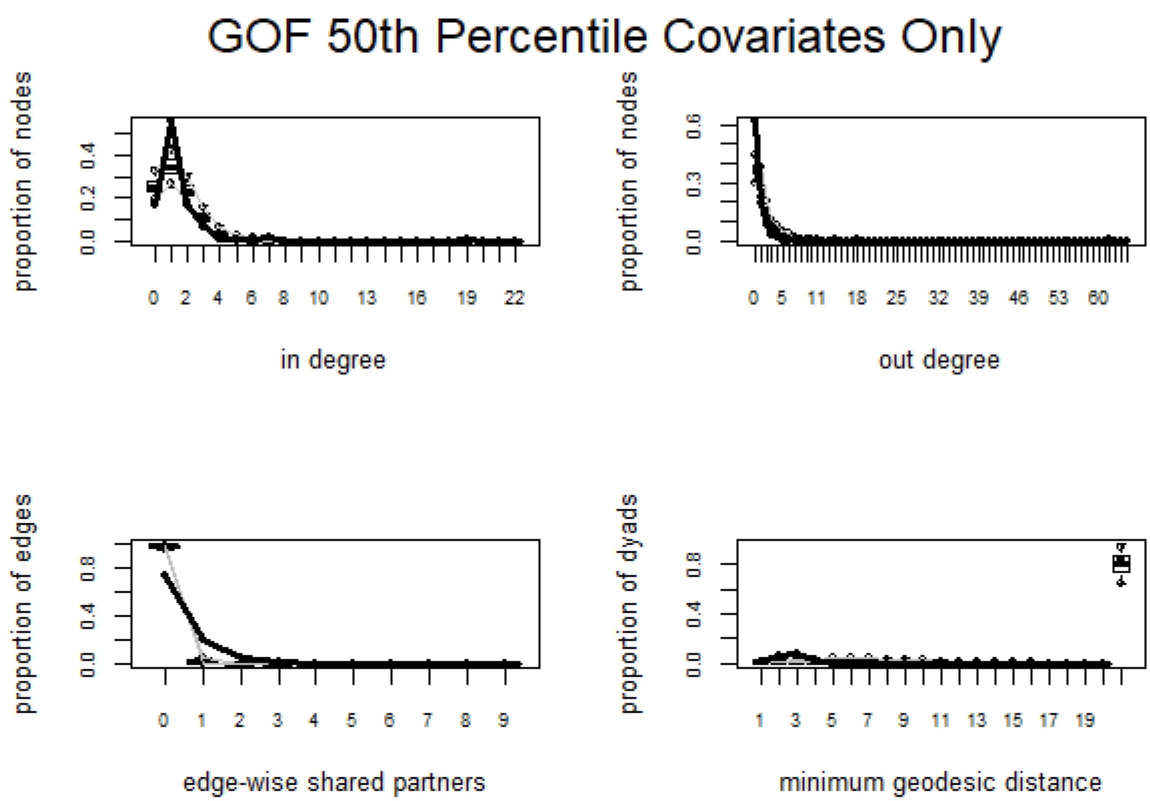
GOF 25th Percentile with Transitivity



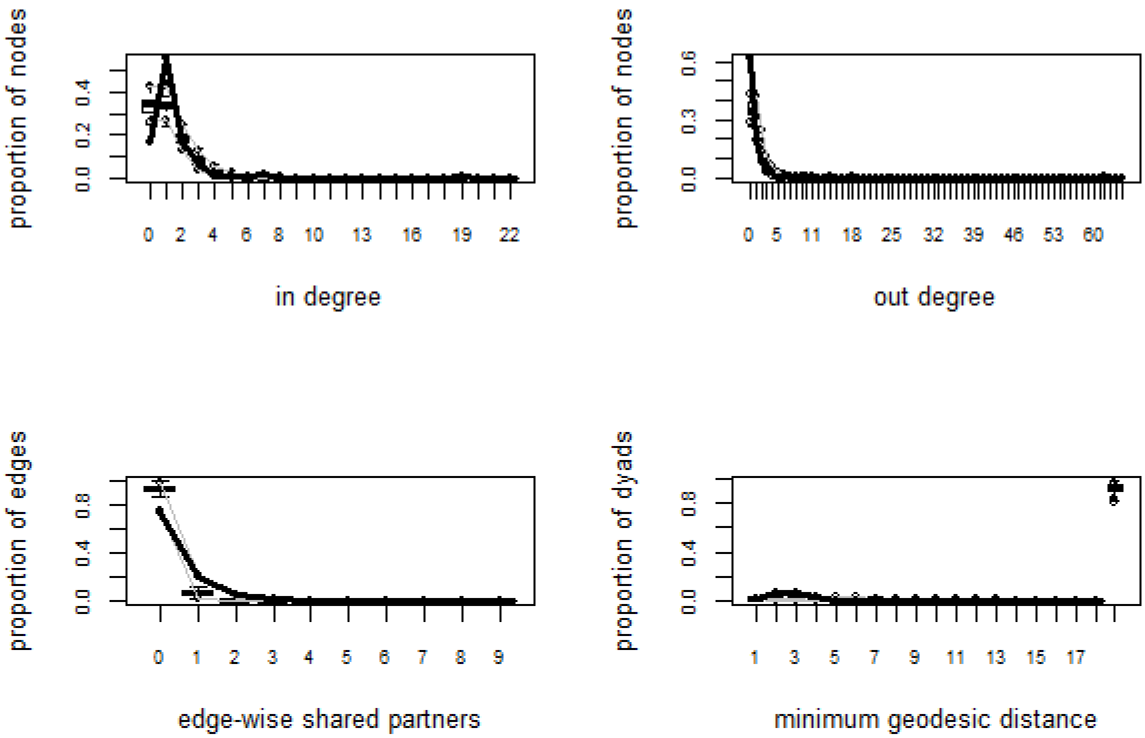
GOF 25th Percentile with Preferential Attachment



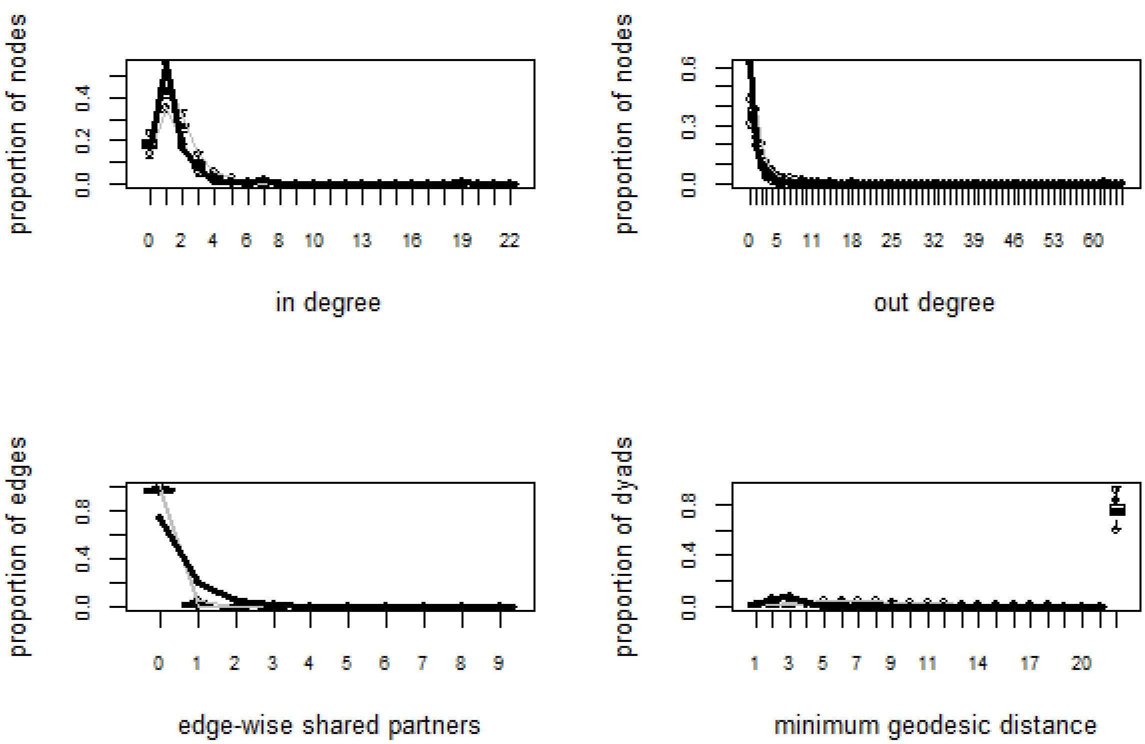

GOF 25th Percentile with Systemic Variables
proportion of nodes
in degree
proportion of nodes
out degree
proportion of edges
edge-wise shared partners
proportion of dyads
minimum geodesic distance
NR

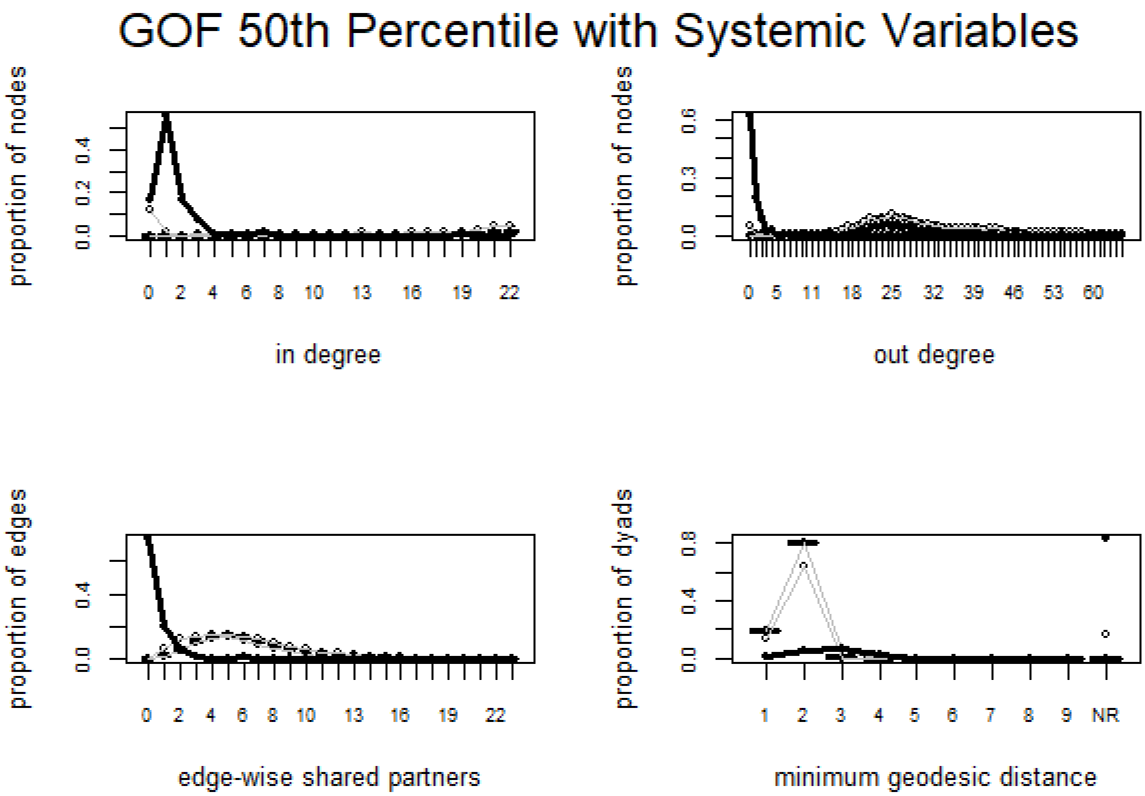

GOF 50th Percentile Covariates Only
proportion of nodes
in degree
proportion of nodes
out degree
proportion of edges
edge-wise shared partners
proportion of dyads
minimum geodesic distance

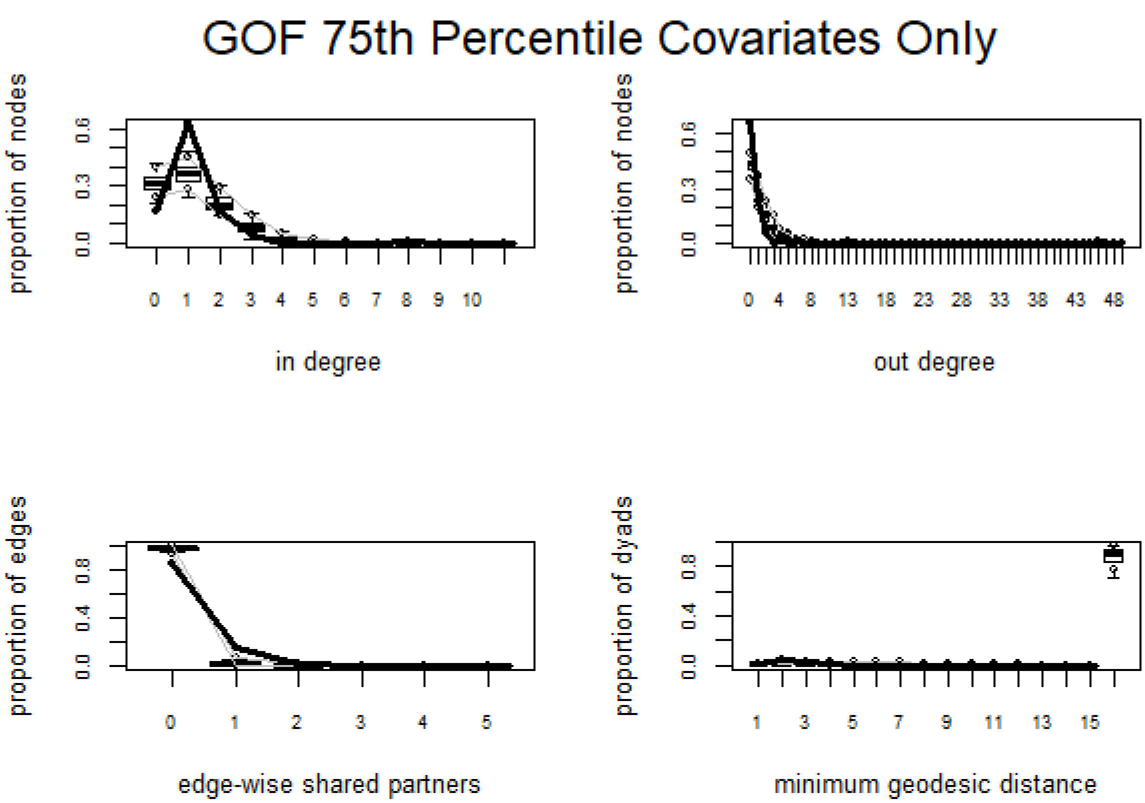
GOF 50th Percentile with Transitivity



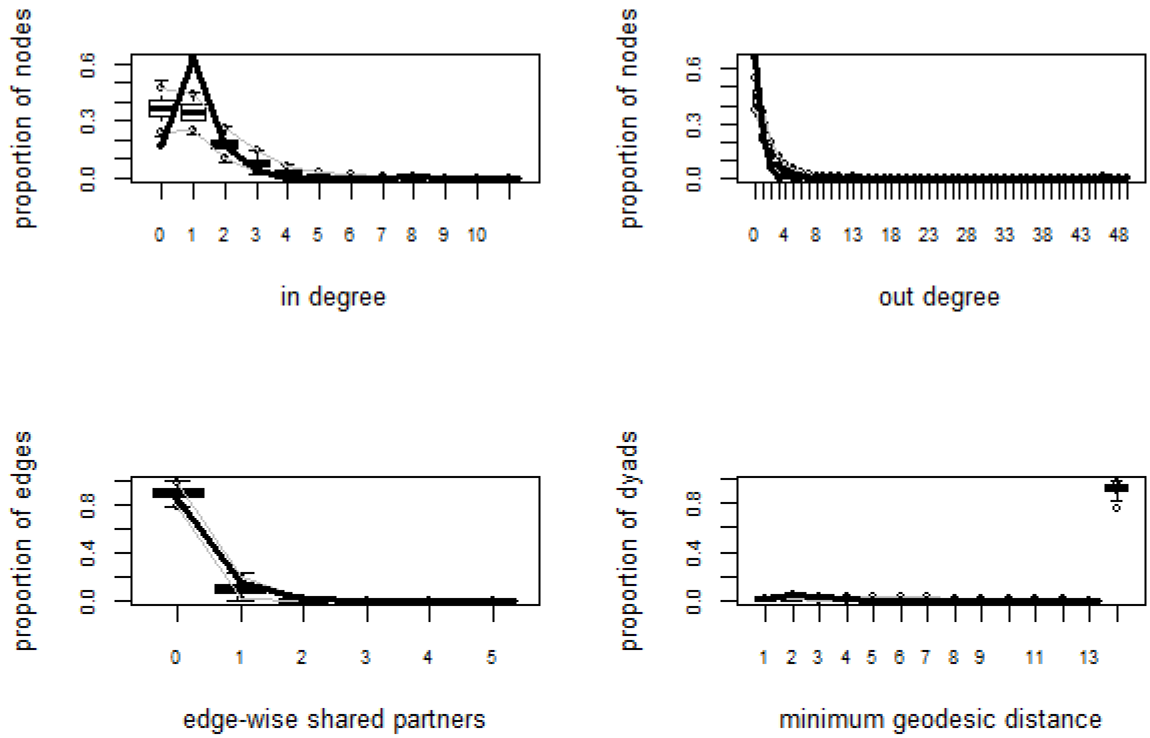
GOF 50th Percentile with Preferential Attachment



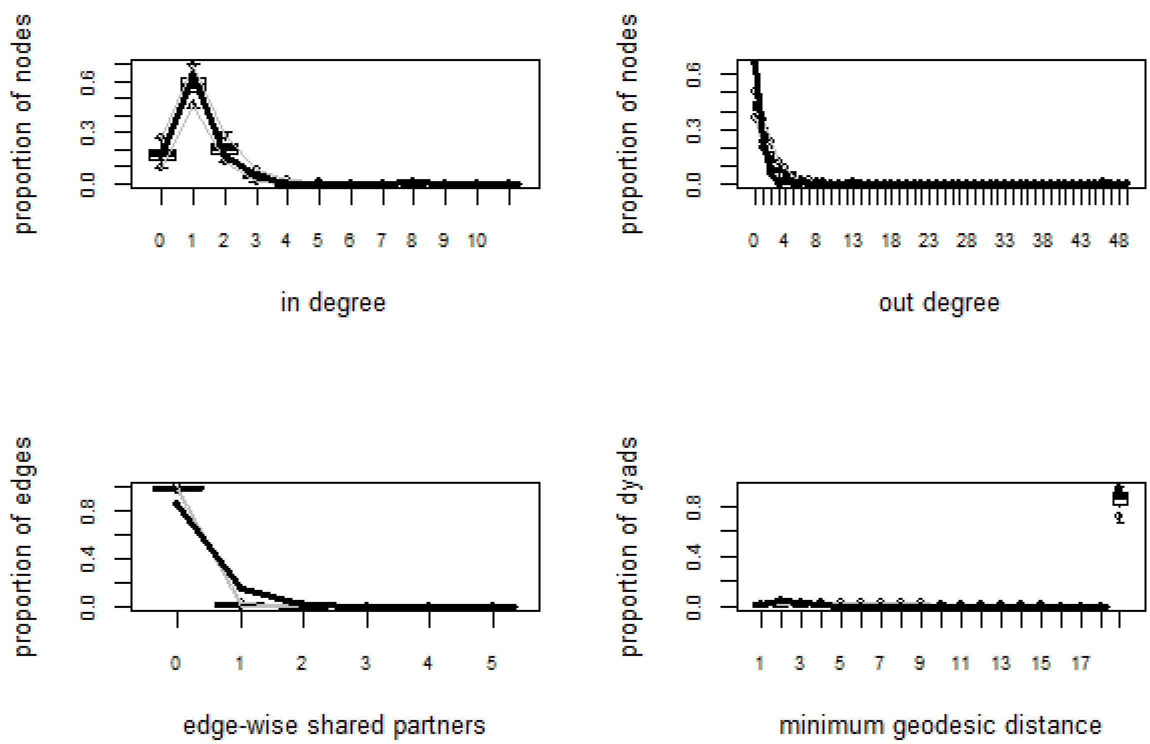

GOF 50th Percentile with Systemic Variables
proportion of nodes
0.0 0.2 0.4
0 2 4 6 8 10 13 16 19 22
in degree
proportion of nodes
0.0 0.3 0.6
0 5 11 18 25 32 39 46 53 60
out degree
proportion of edges
0.0 0.4
0 2 4 6 8 10 13 16 19 22
edge-wise shared partners
proportion of dyads
0.0 0.4 0.8
1 2 3 4 5 6 7 8 9 NR
minimum geodesic distance

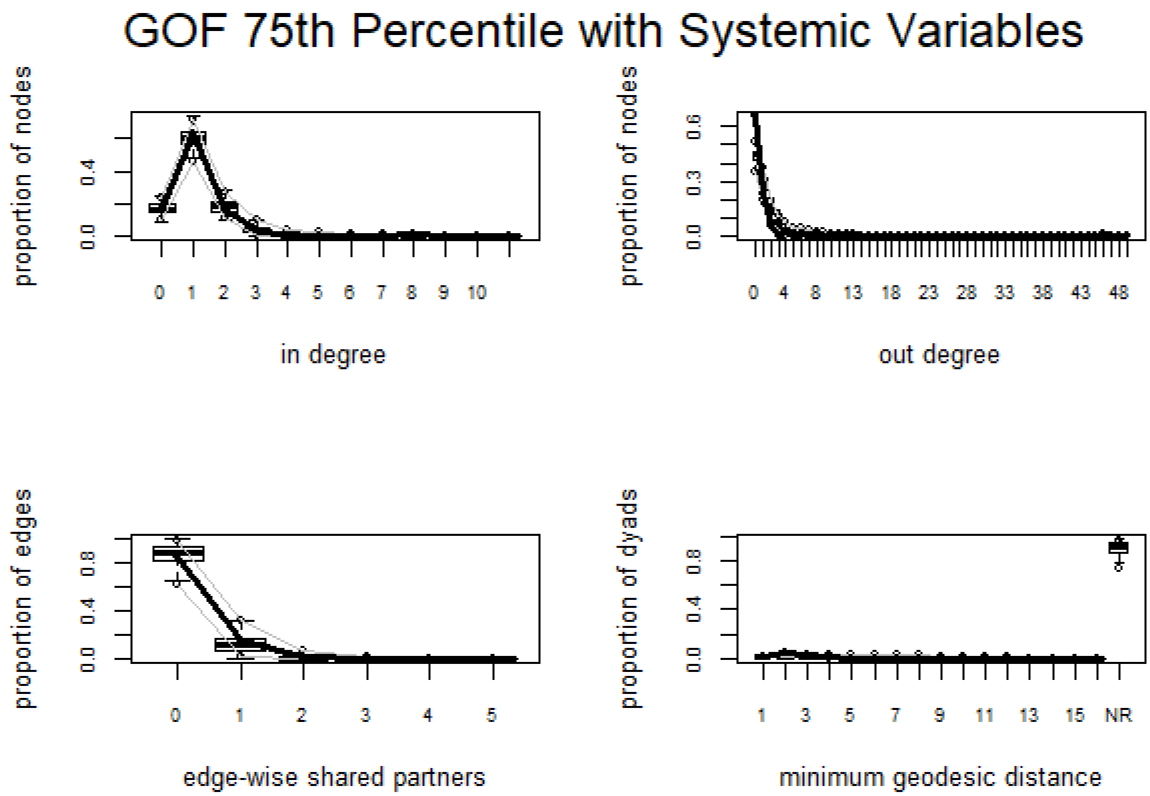

GOF 75th Percentile Covariates Only
proportion of nodes
0.0 0.3 0.6
0 1 2 3 4 5 6 7 8 9 10
in degree
proportion of nodes
0.0 0.3 0.6
0 4 8 13 18 23 28 33 38 43 48
out degree
proportion of edges
0.0 0.4 0.8
0 1 2 3 4 5
edge-wise shared partners
proportion of dyads
0.0 0.4 0.8
1 3 5 7 9 11 13 15
minimum geodesic distance

GOF 75th Percentile with Transitivity



GOF 75th Percentile with Preferential Attachment




GOF 75th Percentile with Systemic Variables
proportion of nodes
0.0
0.4
0 1 2 3 4 5 6 7 8 9 10
in degree
proportion of nodes
0.0
0.3
0.6
0 4 8 13 18 23 28 33 38 43 48
out degree
proportion of edges
0.0
0.4
0.8
0 1 2 3 4 5
edge-wise shared partners
proportion of dyads
0.0
0.4
0.8
1 3 5 7 9 11 13 15 NR
minimum geodesic distance