Network Dynamics of Organized Misconduct

by

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ABSTRACT

This dissertation investigates the effect of social cohesion and structural inequality on the persistence of misconduct communities. Building from nascent work that considers misconduct as an organized phenomenon among multiple actors, I theorize that misconduct communities seek to closely monitor and control community members while minimizing the risk of attention from outsiders. I examine how social cohesion and structural inequality influence these conflicting goals and hypothesize that they each have inverted curvilinear effects on community longevity in that they initially support it but eventually undermine it.

I employ a network community level of analysis to examine how social cohesion and structural inequality influence the persistence of misconduct over time. In the context of misconduct, I argue that these communities balance goals specific to wrongdoing: they attempt to conduct their activities while maximizing internal conformity and coordination and minimizing the risk of interference from outsiders. Specifically, I suggest that the overall social cohesion promotes monitoring and conformity up to a certain point, but eventually becomes a liability by increasing the risk of outsider interference (external risk). Similarly, I suggest that the specific *distribution* of this social cohesion (structural inequality) initially promotes group coordination and efficiency but eventually risks member disengagement and attrition (internal risk).

I test my hypotheses in two unique longitudinal settings. In my first empirical chapter, I use data from 1991 – 2015 on the Chicago Police Department (CPD). I construct a longitudinal dataset of complaints of severe misconduct filed against police officers and identify communities of officers linked together by co-complaints. I use the Louvain community detection algorithm and locate 6,406 unique communities comprised of 8,983 police officers with 11,756 complaints of severe misconduct filed against them. In my second empirical chapter, I leverage data from a long-running white supremacist online chat forum (“Whitestorm”) and similarly use the Louvain algorithm to locate 1,002 unique communities over 11 years of data (2002 – 2012) comprised of 15,956 white supremacists linked by 74,476 threads they share in common. Across both studies,

I operationalize social cohesion as community density (hypothesis 1) and the distribution of that cohesion (structural inequality) as community centralization (hypothesis 2). I define community longevity as retaining some percentage of membership on an annual basis between year1 and year2 and analyze the relationship between my independent and dependent variables at five different retained membership specifications (10 – 50% in ten percent increments).

In the CPD chapter I find that density indeed leads to increased levels of longevity up until a certain point (generally around 60% density), after which it leads to *decreased* longevity. This holds true across all membership thresholds, thereby finding robust support for hypothesis 1. Additionally, I find support for hypothesis 2 in that community centralization first leads with increased levels of community longevity up until a certain point (generally around 40% centralization), after which it leads to *decreased* longevity. This holds true across all membership thresholds.

My results are further supported in the Whitestorm chapter. I similarly find that both density (H1) and centralization (H2) are associated with increased levels of longevity initially but eventually lead to decreased longevity, and at nearly identical inflection points as discovered in the CPD chapter. However, these results are only significant at the 10 – 50% membership thresholds (not 10%). In my discussion section I consider the factors that may explain why a 10% shared membership may not be sufficient to establish community norms in an online setting.

Taken together, my findings in both settings support both hypotheses and suggest indeed a “sweet spot” of community structure that is optimal for prolonged misconduct activity. In doing so, this dissertation proposes a broader theory of organized misconduct and offers an answer to the question: what structural properties influence the persistence of misconduct over time?

Chapter I: Introduction

When a scandal breaks, often the first question asked is, "how did they get away with this for so long?" Many recent high-profile examples reveal pockets of coordinated actors embedded within larger institutional environments who engage in misconduct for long periods of time, such as at Wells Fargo (Corkery, 2016), Volkswagen (Hotten, 2015), and Enron (Aven, 2015; McLean & Elkind, 2013). What enables some such pockets to survive for longer periods of time than others?

While scholars have increasingly focused on the topic of organizational misconduct as its heavy financial, relational, and reputational costs have become clearer (Greve, Palmer, & Pozner, 2010; Palmer, Smith-Crowe, & Greenwood, 2016), an answer to this question remains largely elusive in organizational research. Most research has attempted to understand this issue by exploring the determinants of misconduct, including individual personality traits (Ashkanasy, Windsor, & Treviño, 2006) and situational characteristics (Treviño, den Nieuwenboer, & Kish-Gephart, 2014) that promote misconduct in different settings. However, a growing body of work considers misconduct as a coordinated phenomenon that is socially-embedded within networks (Aven, 2015; Baker & Faulkner, 1993, 2003; Brass, Butterfield, & Skaggs, 1998) and explores the various ego-network attributes (Burt, 1992; Morselli, 2010) and global-network characteristics (Nash, Bouchard, & Malm, 2013; Palmer & Yenkey, 2015) that influence the likelihood of misconduct arising in the first place. While this is important, there have been many calls to better understand not just the relational predictors of misconduct's initiation (Treviño, den Nieuwenboer, & Kish-Gephart, 2014) or proliferation (Ashforth & Anand, 2003; Brief, Buttram, & Dukerich, 2001; Frake & Harmon, 2023), but to specifically capture the structural components of misconduct and how they may contribute to its sustainment over time (Palmer & Moore, 2016; Brass, Galaskiewicz, Greve, & Tsai, 2004; Greve et al., 2010). This dissertation is one such attempt to do so.

In the following two studies, I employ a network community level of analysis to examine how social cohesion and structural inequality influence the persistence of misconduct over time. I build on prior work that defines a community as an interlocking set of proximate social ties that encompass strong norms and monitoring capabilities to ensure conformity to those norms (Marquis, 2003). Empirically, in a network context, a network community is a group situated between the ego- and global-network levels (Newman, 2016) characterized by comparatively strong social cohesion (Granovetter, 1985; Coleman, 1988), the distribution of which varies based on community structure (Marquis, Glynn, & Davis, 2007). In the context of misconduct, I argue that these communities balance goals specific to wrongdoing: they attempt to conduct their activities while maximizing internal conformity and coordination and minimizing risk of attention or interference from outsiders (Baker & Faulkner, 1993; Bertrand & Lumineau, 2016; Morselli, Giguère, & Petit, 2007). Navigating these tradeoffs can pose real risks for communities. For example, investigatory journalist organizations targeted the Chicago Police Department in the early- to mid-2000s to uncover groups of corrupt police officers who engaged in torture, extortion, and bribery to elicit false confessions out of over 400 victim (Kalven, 2016). The work of such outsider groups springboarded several FBI investigations that led to the conviction of several officers involved in these behaviors (Mitchell, 2023; Schulte, 2022). Similarly, posts of white supremacists on online chat forums have attracted the attention of law enforcement agencies that have led to the arrests and foiled plans of several members, including in Italy, France, and the United States (Potok, 2015; Verini, 2023). Thus, the balance between efficiency, effectiveness, and flying under the radar of would-be disruptors is important to the ongoing success of these communities.

Reflecting this delicate balance, I hypothesize that community social cohesion and structural inequality both exert curvilinear effects on community longevity, such that as they each increase, they are initially assets for communities and increase community longevity; however, after a certain point, each of them become a liability and *decrease* community longevity. Specifically, I suggest that the overall social cohesion promotes monitoring and conformity up to a certain point through strong normative cohesiveness, but eventually becomes a liability by increasing the risk of outsider attention. Similarly, I suggest that the specific *distribution* of this social cohesion (structural inequality) initially promotes group coordination and efficiency but eventually risks member disengagement and attrition due to uneven normative constraints.

I test these relationships in two different empirical settings. In my first empirical chapter, I use data from 1991 – 2015 on the Chicago Police Department. I construct a longitudinal dataset of complaints of severe misconduct filed against police officers and identify communities of officers linked together by co-complaints. In line with recent methodological advancements (Jain, Sinclair, & Papachristos, 2022), I use the Louvain community detection algorithm and locate 6,406 unique communities comprised of 8,983 police officers with 11,756 complaints of severe misconduct filed against them. In my second empirical chapter, I leverage data from a long-running white supremacist online chat forum and similarly I use the Louvain community detection algorithm to locate 1,002 unique communities over 11 years of data (2002 – 2012) comprised of 15,956 white supremacists linked by 74,476 threads they post on in common. Across both studies, I operationalize social cohesion as community density (hypothesis 1) and the distribution of that cohesion (structural inequality) as community centralization (hypothesis 2). My findings in both settings support both hypotheses and suggest a "sweet spot" of community structure, highlighting important nuances regarding the structural attributes that support the persistence of misconduct over time.

This dissertation makes several contributions. First, departing from existing work on the antecedents of misconduct, I develop a novel community-based theory of misconduct and explore the structural attributes that contribute to the persistence of misconduct over time. I incorporate recent work exploring the isomorphic pressures within communities and establish the extent to which these pressures may apply in the context of misconduct. Relatedly, most research explores misconduct as a "bad apple" phenomenon at the individual level or considers it a phenomenon within the context of "bad barrels." This dissertation explores misconduct as group-based and thus highlights an intermediate level of analysis between an overly-atomized or -socialized approach. Next, I operationalize misconduct groups as network communities, which remain under-theorized in organizational research despite demonstrating significant potential in shaping key network and organizational outcomes (Sytch & Tatarynowicz, 2014; Gulati & Gargiulo, 1999). Thus, this paper contributes to research on these important sub-structures by quantitatively defining and evaluating the structural features that influence their longevity in the context of misconduct, from which they are largely absent.

Third, this dissertation explores a fundamental sociological question: that is, the institutionalization of norms and behaviors over time (Lawrence & Winn, 2001). A long-standing sociological tradition examines how practices or rules diffuse and become legitimated over time (Leblebici, Salancik, Copay, & King, 1991; Meyer & Rowan, 1977), as well as the extent to which they endure or maintain stability over time (Christensen, 2013; Fligstein, 1991). Longevity has also long been recognized as a fundamental goal for business organizations (Suarez & Utterback, 1995; Barnard, 1938; Dertouzos, Lester, & Solow, 1989). My research explores this topic specifically in the context of misconduct, a setting within which the question of longevity is important, as the risk of significant harm and damage increases the longer misconduct continues (Bertrand & Lumineau, 2016). Fourth, I explore the role of community social cohesion and structural inequality in shaping community longevity. Social cohesion and structural inequality are two key structural characteristics that have been demonstrated to exert contradictory influences on community longevity in a range of contexts, both misconduct-related (i.e., Everton and Cunningham 2015, Wise 2014) and otherwise (i.e., Greve et al. 2010, Rowley et al. 2005, Sytch and Tatarynowicz 2014). This dissertation helps clarify these relationships by offering a unifying theoretical framework and testing my hypotheses in two unique, longitudinal datasets, which has been previously lacking in existing work (Aven, 2015; Aven, Morse, & Iorio, 2019; Palmer & Yenkey, 2015). Finally, this dissertation proposes a broader theory of organized misconduct based on pockets of actors embedded within larger environments hostile to their efforts and offers an answer to the question: what structural properties influence the persistence of misconduct over time? This dissertation thus begins to address important gaps in organizational scholarship and offers a roadmap for future research to further explore the structural underpinnings of prolonged organized misconduct.

Chapter II: Theoretical Background and Hypothesis Development

THEORETICAL BACKGROUND

Misconduct in organizations

Misconduct – activity that violates standards of legality, ethicality, or normative appropriateness – is a significant part of organizational life with heavy costs for firms (Greve et al., 2010; Palmer et al., 2016). Recent wrongdoing scandals revealed at Volkswagen (Hotten, 2015), Wells Fargo (Corkery, 2016), and Enron (Aven, 2015) highlight the reality that misconduct pervades many organizations today. Misconduct is a diverse phenomenon and encompasses activities perpetrated by lone individuals, by a group of actors embedded within a firm, or can be diffuse throughout an entire organization (Graffin, Bundy, Porac, Wade, & Quinn, 2013; Kulik, 2005; Ashforth & Anand, 2003). Regardless of type, misconduct reflects a foundational component of social life (Coleman, 1990; Durkheim, 1938): that is, issues of social order and the subversion of it.

In an effort to understand why misconduct is so prevalent, organizational scholars have explored many of its determinants. Many individual attributes have been linked to a higher likelihood of engaging in misconduct (Kohlberg, 1976; Treviño & Youngblood, 1990). In contrast, other research has demonstrated that many organizational and institutional characteristics can promote misconduct (Arrow, 1963; Hegarty & Sims, 1978; Punch, 1985). Taken together, this body of work suggests that concrete attributes at the individual (micro) and situational (macro) levels can induce misconduct. While this is important, a growing body of work offers a more dynamic approach and leverages a network lens to explore misconduct at the meso level, which helps straddle the under-socialized view of individuals acting in isolation and the over-socialized view of individuals obedient to their environment's norms and culture (Granovetter, 1992; Jones, 1991). This line of research focuses on relationships among actors and examines relationship structures that can lead to misconduct.

A network view of misconduct

Social network research on misconduct is "embryonic but growing" (Palmer & Moore, 2016: 203). Most network research explores the role of ego-network attributes or global-network characteristics that influence the initiation or prevalence of misconduct. Ego-based work explores how node position can influence wrongdoing (Everton, 2012; Brass et al., 1998) and has demonstrated, for example, that actors who are more centrally-positioned in their network are more likely to engage in misconduct (Morselli, 2010; Calderoni, 2012). Also, actors who are uniquely positioned between other actors who don't know each other (i.e., have higher betweenness centrality) are more likely to engage in misconduct (Janis, 1983) as they are more able to take advantage of information imbalances within their local network (Burt, 1992).

In contrast, other work examines global-network characteristics that influence the prevalence of wrongdoing (Cunningham, Everton, & Murphy, 2016), such as the distribution of strong ties or high density among wrongdoers. This research suggests that misconduct more easily spreads through a tightly-connected network (Aven, 2015; Nash et al., 2013). Ahern (2017), for example, found that insider traders spread information through their strong social connections. This research also suggests that being directly tied to others engaging in misconduct increases one's propensity to do so as well, as O'Fallon and Butterfield (2012) found with undergraduates' likelihood of cheating on exams.

While existing work is promising, there have been many calls to better understand the structural components of misconduct and how they may contribute to its sustainment over time (Greve, Palmer, et al., 2010; Brass et al., 2004; Zuber, 2015). Specifically, Palmer and Moore (2016) note that temporal social network dynamics likely influence misconduct’s persistence. Thus, the persistence of misconduct through a structural lens remains an open question in organizational research. In an effort to address this, I develop a community-based theory to explore how misconduct may persist over time.

Misconduct can come in many forms: it can be perpetrated by lone actors seeking their own gain, such as with Bernie Madoff (Gibson, 2014); it can be interwoven into an organization’s very purpose, as is seen with the Mafia, drug cartels, or terrorist groups (Calderoni, 2012; Shapiro, 2013); or it can exist among pockets of actors embedded within a broader organizational context (Aven, 2015; Baker & Faulkner, 1993). This dissertation focuses on the latter and considers how these pockets, or communities, engage in ongoing misconduct while navigating a larger environment that is, to varying degrees, hostile to their behaviors.

Communities as institutional forms

The concept of a community has long been debated in sociology (Mulligan, 2015). A community can be conceived of as a shared sense of place, traditionally considered through a geographic or physical lens (Lounsbury, 2007; Marquis & Battilana, 2009). It can also be conceptualized based on social interaction and exchange of social capital, in which resources flow between socio-expressive or instrumental ties (Coleman, 1987; Edwards & Foley, 1997, 1998; Putnam, 1995). Or, the concept of a community can be considered more symbolic in nature and apply to individuals organized around a common set of values, beliefs, norms, or interests (Cohen, 2015; Becker & Horowitz, 1971; Kanter, 1972; Zukin, 1996). A community viewpoint can apply to many different types and sizes of groups, from classrooms, to academic departments, to places of worship, universities, to states or even nations as a whole (Anderson, 1991; Cnaan & Milofsky, 2007). Though the exact definition may vary across sociologists and organizational scholars, overall a community can be thought of as a type of identification or belongingness that emerges through affiliation, based on membership to that community (Jeppesen & Frederiksen, 2006; Almandoz, Marquis, & Cheely, 2017; Mok, Wellman, & Carrasco, 2010).

A recent tradition has extended institutional theory to communities as distinct institutional orders that influence behavior (Marquis, Lounsbury, and Greenwood, 2011). A community is characterized by interlocking sets of proximate social ties in a network (Marquis, 2003) that constitute a local source of institutional pressures that give rise to and structure the behaviors of actors within that community (Marquis, Glynn, and Davis, 2007). These communities are often characterized as being locally dense with sparse ties to other areas (Stinchcombe, 1965; Uzzi, 1997), and reflect a group of actors that share elements of local culture, norms, and expectations (Marquis and Battilana, 2009). Examples of communities include academic communities (Crane, 1969; Knorr-Cetina, 1999), collaborative communities (Adler, 2001; Heckscher & Adler, 2006), or occupational communities (Bechky, 2003; Orr, 1996). These localized contexts provide actors with salient definitions of appropriateness (Strang and Meyer, 1993; Gulati and Gargiulo, 1999) that serve as touchstones for directing and legitimizing behavior through isomorphism (DiMaggio and Powell, 1983; Marquis and Battilana, 2009). Early institutional work, such as Tonnies' (1887) work distinguishing the concept of a "community" as a category of meaningful social relationships, Selznick's (1949) study of the

Tennessee Valley Authority, and Zald's (1970) study of the Chicago YMCA, demonstrate that behavior is heavily influenced by local norms and expectations.

The local embeddedness of actors within communities gives rise to distinct cultural and normative environments that determine appropriate behaviors as defined by their specific community (Marquis and Tilcsik, 2016; Greenwood et al., 2011; Greenwood and Meyer, 2008). Consistent with new institutional theory (Scott, 2001), many researchers have demonstrated how members of social networks rely on proximate actors as models for legitimacy and action (Davis and Greve, 1997). For example, prior work indicates that a community lens may help us understand the behavior in a variety of contexts including biotechnology partnerships (Walker, Kogut, and Shan, 1997), the Broadway musical industry (Uzzi and Spiro, 2004), and board director ties in Minneapolis (Galaskiewicz, 1997). Additionally, research suggests that the local environment may be particularly powerful in influencing behavior when a practice is contentious (Margolis and Walsh, 2003). For example, Davis and Greve (1997) note that corporate boards were more likely to adopt a golden parachute practice depending on the actions of other locally-headquartered companies. Reflecting this, Useem (1988: 83) posits that local norms and attitudes are perhaps the "most significant factor" shaping behavior within that community, regardless of the broader institutional environment in which they may be embedded.

A network community approach

Existing work suggests that misconduct can be perpetrated by smaller sub-groups of actors within a broader organizational setting (Palmer & Yenkey, 2015; Wang, Stuart, & Li, 2021; Zhang & King, 2021). These sub-groups can be classified as network communities: locally-dense, non-overlapping social structures that are sparsely (or entirely non-)connected to other sub-groups within a larger network (Girvan & Newman, 2002; Newman & Girvan, 2004). Network communities are common network features and are found in many different types of network systems, including among corporations (Nohria & Garcia-Pont, 1991), state authorities (Laumann, Galaskiewicz, & Marsden, 1978), and elites (Laumann & Marsden, 1979). Indeed, this level of analysis is commonly leveraged in interfirm alliance research (i.e., Greve, Baum, et al. 2010, Rowley et al. 2005, Sytch and Tatarynowicz 2014) as a way of tracing the duration of these subgroups over time.

In considering misconduct as a relational phenomenon, I seek to understand the structural properties that contribute to community longevity. I incorporate an institutional perspective and suggest that misconduct communities – that is, communities defined by misconduct relationships among actors – are similar to other types of communities and exert their own normative pressures and monitoring capabilities to enforce conformity among members. While these pressures can lead to positive outcomes such as improved loyalty and coordination, these same structural features can also threaten the community longevity as such features increase the likelihood of attention and disruption from outsiders, and also influence the likelihood of internal dissention, factionalizing, and departure.

Social cohesion and structural inequality are two key structural characteristics that have been demonstrated to exert contradictory influences on community longevity in a range of contexts, both misconduct-related (i.e., Everton and Cunningham 2015, Wise 2014) and otherwise (i.e., Greve, Baum, et al. 2010, Rowley et al. 2005, Sytch and Tatarynowicz 2014). I expect for misconduct communities, the localized normative pressures and monitoring abilities will be an advantage or disadvantage depending on both the overall social cohesion of the group as well as the distribution of that cohesion among members.

HYPOTHESIS DEVELOPMENT

Social Cohesion

First, sociologists have long considered the impact of actors' local environment in shaping behavior. Granovetter (1985: 488) asserted that actors are embedded in "concrete, ongoing systems of social relations" that establish appropriate norms and thus constrain behavior. Coleman (1988) similarly established that the relationship structures among actors reinforces norms, which facilitate certain behaviors and constrain others. Particularly, as the cohesion (density) of relationships among actors increases, so too do obligations of reciprocity, thereby further entrenching actors in the expectations of their local environment (McPherson & Smith-Lovin, 2002).

Research indicates that the social cohesion engendered by dense connections builds familiarity and norms. Though communities, by definition, have higher density than the overarching structure in which they are embedded, their density does vary based on their structure (Vedres & Stark, 2010). Norms are more powerful in denser communities as the higher degree of interconnectedness better enables members to collectively monitor behavior (Walker, Kogut, & Shan, 1997). This cohesion acts as an effective governance mechanism that both establishes norms and deters norm violation through sanctioning (Aven et al., 2019; Axelrod, 1984; Podolny, 1993). Cohesion becomes constraining because it strengthens (or weaken) expectations about member behaviors as well as the mechanisms for spreading information about that behavior. Thus, as a community's level of social cohesion increases, its ability to establish cooperative norms as well as collective monitoring also increases (Coleman, 1988; Baum, McEvily, & Rowley, 2007; Rowley, 1997; Greve, Baum, et al., 2010).

However, while social cohesion tends to establish effective sanctions that monitor and guide behavior (Coleman, 1990), thus improving group stability (Krackhardt, 1998; McPherson & Smith-Lovin, 2002; Lawler & Yoon, 1996), there is reason to believe it may run counter to a misconduct community's continued longevity. Similar to a secret society (Simmel, 1906) or so-called "dark networks" (Cunningham et al., 2016; Everton, 2012), research suggests that misconduct-based communities attempt to manage tensions between operating efficiently while maintaining some degree of protection from outsiders who might be interested in disrupting their behaviors (Crossley, Edwards, Harries, & Stevenson, 2012; Morselli et al., 2007; Baker & Faulkner, 1993). Indeed, while some research indicates that misconduct communities strive to cultivate sparser relationship structures to avoid attention from outsiders (Erickson, 1981), other work indicates that such communities prioritize denser relationships to maximize efficiency. Thus, while social cohesion can benefit a community's ability to coordinate effectively (Shapiro, 2013), it also increases the likelihood of outsider attention and thus risks interference.

Communities act as local normative environments that define what is appropriate and attempt to control members' behaviors in accordance with those rules. As member behaviors begin to reflect an increasingly discernable pattern of broader misconduct relationships, the likelihood of attracting interest and attention of external social control agents increases. Thus, a group that is more cohesive is more likely to draw attention from external control agents who may become more motivated to interfere with the activities of the community. In the case of the CPD, highly-dense communities who keep getting serious complaints with each other are more likely to draw attention to themselves from would-be interferers (such as supervisors or the media; see Hannigan, Bundy, Graffin, Wade, & Porac, 2015; Meier & Johnson, 1977; Greve & Teh, 2016), as compared to lone actors or officers who experience one-off co-accusals.

Similarly, in the case of Whitestorm, highly-dense communities reflect more repeat activity among the same members, who are thus more likely to get attention from possible SCAs (who notoriously lurk, such as the FBI), versus loosely-connected or one-off member exchanges (Holt, Chermak, & Freilich, 2021). Such communities reflect a grey-area of organizational misconduct in which groups are not necessarily prioritizing absolute concealment as much as attempting to fly *sufficiently* under the radar of potentially hostile outsiders.

As a community's social cohesion increases, it influences its ability to effectively react to these hostile outsiders. With an increase in outsider attention –and possible motivation for disruption – the environment within which the community is operating has now shifted, and the community's ability to adapt to that environmental shift becomes paramount (Hannan & Freeman, 1977, 1989). Unfortunately, the cohesion that has helped the community up until this point now becomes a hindrance. An increasingly cohesive community is also an increasingly isolated one. Communities with higher levels of isolation are unlikely to sustain over the long term (Jackson, Petersen, Bull, Monsen, & Richmond, 1960) as links to outsiders helps them gain access to important information and other resources necessary (Everton & Cunningham, 2015). Specifically, such external ties are vital for survival in a rapidly changing environment (Uzzi, 1996, 2008; Uzzi & Spiro, 2005), as becomes the case once a community's structure has tipped into the notice of hostile outsiders.

In an effort to capture these tensions between social cohesion as both a helpful and harmful element to community longevity, I expect that social cohesion will initially benefit communities up to a certain point and increase community longevity, after which the risks outweigh the benefits and it will decrease community longevity. I therefore hypothesize:

> **Hypothesis 1 (H1):** As community social cohesion increases, community longevity increases up until a certain point, after which, community longevity decreases.

Structural Inequality

While the overall social cohesiveness of a community is important for its survival over time, it is important to also consider the *distribution* of this cohesiveness among members, as it may vary by position. The extent to which specific members are directly tied to other members within a group varies: certain members are likely to hold more direct ties than others (Uzzi, 1997), and this pattern of ties is reflected in a community's graph centralization, or its structural inequality (Freeman, 1978, 2014). Within a social capital framework, network positions exert asymmetric constraints to community members depending on the extent to which they are embedded within the community's normative environment. Structural inequality captures the specific distribution of ties at the community level and thus reflects structural asymmetries among members. Specifically, a more structurally unequal community structure reflects wider disparity among members and is likely to reflect uneven patterns of norm constraint and monitoring experienced by members, while a more structurally *equal* community structure reflects less disparity among members and is likely to more evenly constrain actors through norms and monitoring mechanisms to ensure conformity (Erickson, 1981). Depending on the structural inequality of a community, different members will be differently embedded in – and thus, constrained by – the norms and monitoring capabilities of the community (Wasserman & Faust, 1994; Burt, 2002).

The extent to which a community exhibits more or less structural inequality can influence community stability (Bertrand & Lumineau, 2016; Rowley et al., 2005). Specifically, the power of community norms and monitoring capabilities depends on the relatively equal distribution of ties in the community: effective norm distribution is most likely to occur when multiple members experience similar levels of normative constraints (Burt, 1992b; Coleman, 1990). If a community's centralization increases – reflecting more structural inequality among members – the community may become more at risk of losing less-entrenched members, thus possibly disrupting community structure and making it vulnerable to disintegration (Greve, Baum, et al., 2010). Thus, a more *de*centralized group structure (one that is more structurally *equal*) both can act as a protective mechanism from would-be interlopers, while also promoting a sense of belongingness and "we're all in this together" with equal risk and equal monitoring shared among all members (Everton & Cunningham, 2015).

At the same time, structural inequality does have many benefits. It promotes coordination among members through low average path lengths, meaning that most members can be reached either directly or through a few intermediaries (DellaPosta, 2017; Faulkner, Cheney, Fisher, & Baker, 2003). It also can help communities be more efficient (Morselli, 2009) and mobilize key resources (Enders & Jindapon, 2010). This kind of functionality is important for communities that balance security needs with a desire to follow orders from key figureheads who communicate and ensure adherence to community rules and expectations (Crossley et al., 2012; Everton & Cunningham, 2015; Morselli et al., 2007). Thus, misconduct communities are likely to balance tradeoffs that come with different degrees of structural inequality. On one hand, while a structurally equal community is less vulnerable to outsider disruption due to fewer direct ties, it is likely less efficient. On the flip side, a structurally unequal community is more vulnerable both to outsiders as well as internal factionalizing, but is likely more well-run.

Ultimately, as a community's structural inequality increases, its ability to effectively react to uncertain and hostile outsider forces decreases (Hannan & Freeman, 1977, 1989). Research suggests that less-centralized organizations are better able to adapt more quickly to rapidly changing environments (Arquilla, 2009), as is the case for communities attempting to minimizing outsider notice (Everton, 2012; Uzzi, 1996, 2008). For example, many such communities often adopt cellular forms of network structure (Carley, Dombroski, Reminga, & Kamneva, 2003) which allowed them to more easily adjust to shifting environments than would more centralized networks (Kenney, 2007). Thus, I therefore expect that structural inequality will have a curvilinear effect on community longevity such that it will, up to a point, increase community longevity as it will promote overall community function. However, past a certain point, I expect that structural inequality will lead to a decrease in community longevity as the risks of destabilization and factionalizing will outweigh the benefits that come with increased structural inequality. I therefore hypothesize:

> **Hypothesis 2 (H2):** As community structural inequality increases, community longevity increases up until a certain point, after which, community longevity decreases.

I test these hypotheses in two different empirical settings, each of which explores high-stakes misconduct as the basis for misconduct network communities. In the following chapters, I explore community social cohesion and community structural inequality as key drivers in the extent to which a community survives over time. My findings across both settings support my hypotheses and indicate a curvilinear relationship such that these attributes are initially assets but eventually become liabilities for misconduct communities. In my concluding chapter, I compare and contrast the findings from these studies and offer theoretical generalizations and chart a path forward towards building a theory of organized misconduct that transcends context.

Chapter III: Hanging Together: The Persistence of Misconduct Communities in the Chicago Police Department

INTRODUCTION

In this study, I employ a network community level of analysis to examine how social cohesion and structural inequality influence the persistence of misconduct over time. I examine these relationships using longitudinal data from 1991 – 2015 on the Chicago Police Department. I construct a longitudinal dataset of complaints of severe misconduct filed against police officers and identify communities of officers linked together by co-complaints. I use the Louvain community detection algorithm and locate 6,406 unique communities comprised of 8,983 police officers with 11,756 complaints of severe misconduct filed against them. I operationalize social cohesion as community density (hypothesis 1) and the distribution of that cohesion (structural inequality) as community centralization (hypothesis 2).

EMPIRICAL SETTING AND DATA

"Police are not protecting our city when they see something and say nothing… I am looking for a new leader of the Chicago Police Department to address the problems at the very heart of the policing profession. This problem is sometimes referred to as the 'thin blue line.' Other times it's referred to as the 'code of silence.' It is the tendency to ignore, deny, or in some cases cover up the bad actions of a colleague or colleagues."

- Chicago Mayor Rahm Emanuel, in response to the police killing of Laquan McDonald, December 2015

"The City, police officers, and leadership within CPD and its police officer union acknowledge that a code of silence among Chicago police officers exists, extending to lying and affirmative efforts to conceal evidence… One CPD sergeant told us that, 'if someone comes forward as a whistleblower in the Department, they are dead on the street.'"

- United States Justice Department investigation of the Chicago Police Department in response to the killing of Laquan McDonald, January 2017 (p. 75)

The Chicago Police Department (CPD) is the second-largest police department in the US with an annual operating budget over nearly two billion dollars (Police Accountability Task Force, 2016). This is a promising setting within which to explore dynamics of misconduct communities for a few reasons. A recent report from the United States Department of Justice (2017) details the repeated, frequent, and widespread instances of misconduct among CPD officers, including excessive use of force and derogatory behaviors towards civilians. Indeed, the CPD has a long history of misconduct and corruption (Gonzalez van Cleve, 2016). As the CPD is a context where misconduct is an acute problem with negative consequences for organizational members and the broader population (Thomson-DeVeaux, Bronner, & Sharma, 2021), it thus encompasses an ideal setting within which to study this topic.

Key terms and level of analysis

Misconduct

I define misconduct as a wide range of behaviors that violate standards of appropriateness, ethicality, legality, or normative legitimacy (Greve, Palmer, et al., 2010; Palmer, Smith-Crowe, & Greenwood, 2016b). In this study I operationalize misconduct as complaints filed against police officers. In the CPD, complaints can be filed by officers or civilians and are reported to the Independent Police Review Authority (IPRA)[1]. Complaints are received by phone, mail, in person, or online, and must include a sworn affidavit from the

[1] In 2017, the IPRA's investigative duties were reassigned to a new organization called Civilian Office of Police Accountability (COPA). Prior to 2007, an agency called the Office of Professional Standards (OPS) investigated serious complaints against officers, including those involving death, severe injury, excessive use of force, or improper search and seizure.

complainant certifying that the accusation is factual. Once a misconduct complaint is received, the IPRA notifies the implicated officer(s) and begins the investigatory process. Investigators collect evidence and conduct interviews to assess guilt. If investigators find sufficient evidence to justify disciplinary action, the complaint becomes “sustained” and a disciplinary recommendation is made to the CPD Superintendent. Disciplinary actions include: violation noted (no disciplinary action); reprimand (written and/or verbal); suspension; or termination.

There are a few limitations with operationalizing misconduct in this way: namely, that it may either *under*estimate the true extent of misconduct due to barriers of reporting, or that it may actually *over*estimate misconduct by capturing “normal” police activities. Some research suggests that only one-third of all people who believe they were mistreated by police actually file a complaint (Walker & Bumphus, 1992). Additionally, the process of filing a complaint itself may discourage individuals from doing so as it can be intimidating and complicated (Ba, 2018). Indeed, at the time of filing a complaint with the CPD, complainants are reminded in the affidavit that knowingly false statements are subject to criminal prosecution. In contrast, other research notes that what a civilian believes to be misconduct may not actually violate any law or rule, but may instead merely represent normal officer activity rather than misconduct (Lersch, 2002). This line of research notes, for example, that officers in high-crime areas are more likely to receive complaints even if those complaints cannot later be linked to actual misconduct (Terrill & McCluskey, 2002).

However, despite these limitations, I argue that complaints are a reasonable proxy for misconduct. First, there is evidence that complaints do indeed capture problematic police behavior and misconduct (Terrill & Ingram, 2016). Specifically, Rozema and Schanzenbach (2019) demonstrate a relationship between civilian complaints and future civil litigation, and other research shows a strong correlation between civilian-filed complaints and complaints filed by the internal affairs office within police departments (Lersch & Mieczkowski, 2000; Wood, Roithmayr, & Papachristos, 2019). Additionally, the investigatory body that determines whether complaints are worthy of punishment is notoriously non-independent and therefore has a vested interest in keeping punishments as few – and as lenient – as possible (Stroube, 2021; Kalven, 2016). Thus, complaints of misconduct (rather than, for example, *sustained* complaints) constitute an appropriate measure and, per other researchers, is my best attempt to unearth patterns of misconduct in this setting (Lersch, 2002; Terrill & McCluskey, 2002; Kane, 2002; Rozema & Schanzenbach, 2019).

Misconduct Communities

I use network communities as my empirical measure for locating misconduct groups within the CPD. I define misconduct groups as groups of actors tied together by misconduct activities – in this case, by complaints of severe misconduct filed against them. Recent work suggests that police misconduct involves extradyadic patterns to form clusters of “larger collective patterns of misconduct” (Wood et al., 2019: 13). For example, Jain and colleagues (2022) recently found that a network community approach accurately captured several well-known “crews” in the CPD – large groups of officers engaged in coordinated, large-scale misconduct over time – and demonstrated that direct and indirect ties via shared complaints among officers capture real misconduct relationships. Thus, in line with this nascent work, I construct network communities by capturing ties between officers based on misconduct complaints they share in common.

Data and Sample

I procured my data through the Invisible Institute[2], an independent investigative journalism nonprofit based in Chicago that advocated for these complaint records to become public.[3] The data include information on officers such as demographics, rank, unit assignments, misconduct incidents, and outcomes of misconduct complaints.[4] Most relevant to my research question, these data include incidents that involve co-complaints—that is, two or more officers who are linked by their joint involvement in the incident.

My sample consists of officers who received severe misconduct complaints between 1991 and 2015. This data reflects 71% of cases reported in the CPD Annual Reports and includes details on both officers and complaints. Complaints filed with the CPD range from behaviors including excessive force, improper arrest procedures, or civil rights violations, to personnel violations such as filing paperwork incorrectly, wearing one's uniform improperly, and tardiness. Given the potential for harm and even death resulting from some forms of police misconduct, I focus only on complaints I define as "severe." I define severe misconduct as comprised of eight sub-categories of complaints: (1) arrest-related behaviors, including roughing or harming the arrestee before, during, or after arrest, or performing an illegal arrest; (2) excessive force, including unnecessary use of firearm or physical contact while on or off-duty, and while during an arrest or not; (3) acting without a warrant, including illegally searching a person or property during an arrest or not; (4) violating civil rights, including violations of the first amendment, unlawful arrest, or illegal search; (5) bribery, including bribing officials or receiving bribes from

[2] Data can be found at https://github.com/invinst/chicago-police-data/tree/master/data.
[3] After filing a lawsuit in 2007, the Illinois Supreme Court ruled to make complaint records public in 2014. While the CPD Union appealed the decision, it was finalized in 2016 and the records became available to the public at that time.
[4] Details for undercover officers and misconduct complaints involving minors are redacted.

others, or extortion; (6) commission of crime, including arson, assault, trespassing, or theft; (7) racial profiling; and / or (8) sexual harassment / assault. Some complaints were classified across multiple categories. **Table 1** includes summary statistics regarding severe complaint data.

Empirical Approach

Identifying network communities.

One of network science's foundational tasks is to identify and analyze meaningful subgroupings of individuals within larger networks (Getty, Worrall, & Morris, 2016). There are several different techniques that detect subgroups or clusters within larger networks. However, identifying groups related to wrongdoing is particularly difficult, as data on such groups is incredibly difficult to obtain and such groups generally go to great lengths to conceal their behaviors (Morselli, 2009; Baker & Faulkner, 1993). Nevertheless, a few recent studies have attempted to identify communities within larger criminal networks, and I am guided by these attempts. Prior work has used community detection algorithms to look for subgroups within the Ndrangheta mafia organizations in Italy (Calderoni, Brunetto, & Piccardi, 2017), as well as within two criminal networks, the Ndrangheta and a Canadian drug trafficking network (Bahulkar, Szymanski, Baycik, & Sharkey, 2018). While there are several possible algorithmic approaches, recent work by Jain and colleagues (2022) determined that the Louvain algorithm was best-suited for a Chicago Police Department dataset similar to my own, as it significantly outperformed three other algorithms in detecting known "crews" and predicting the likelihood that other located communities may also be crews. Thus, reconstructed the co-accusal network beginning in 1991 and apply the Louvain algorithm to locate communities in 25 yearly observations of the evolving network until 2015.

The Louvain algorithm identifies communities by assessing the difference in community structure between the actual network and a random network of the same size and degree distribution. The algorithm quantifies this difference as "network modularity," which is the total number of ties in the network compared to the expected number of such ties in the random network. Modularity is maximized over all possible community assignments and compared to a large number of random networks for assessment of its statistical significance, generating a statistically validated partition of the network (Guimerà & Nunes Amaral, 2005). Values greater than 0.3 typically indicate a strong degree of community structure that could not be obtained by chance (Newman, 2006).

To analyze the network of officers with severe misconduct accusals, I constructed ties between officers based on whether they shared a complaint in common, and then translated this two-mode network (officers and complaints) into a one-mode matrix of officer X officer shared complaints in ORA-PRO version 3.0.9.134, wherein the nodes are officers and the links are complaints they share in common. In constructing these matrices, I first examined the global network of 58,030 severe complaints filed against 12,997 police officers from 1991 to 2015. My analyses of the global network revealed the existence of a strong community structure throughout the period of the study. The value of modularity varied between 0.60 in 1991 and 0.97 in 1998, averaging 0.94 over all 25 years, therefore substantially exceeding the recommended threshold of 0.3. I located 25,496 distinct communities averaging 2.6 officers (ranging from 1 – 188 officers). The mean density of ties within these communities was 0.42, while the mean density of ties in the global network was 0.002. Overall, these results confirmed my expectation that the identified communities indeed reflected pockets of strong relational cohesion among officers (Sytch & Tatarynowicz, 2014). **Figure 1** shows a sample of the global network in 2000.

While this was an important first step, the global network is not the final sample with which I test my hypotheses for a few reasons. First, the nature of policing is generally grouped based on unit assignments. Thus, some officers may be linked to communities through chance or simply based on their formal assignment and may not be actually part of any misconduct or illegal behavior themselves. Relatedly, some communities may simply be a byproduct of the larger organizational structure rather than subgroups of officers repeatedly and intentionally engaging in coordinate misconduct. Mirroring recent work by Jain and colleagues (2022), I employed a few different techniques to attempt to mitigate this empirical challenge.

First, I removed any officers in my dataset who only receive one total complaint over the course of their career, as such officers are likely not a part of coordinated misconduct relationships. Next, I removed isolates and dyads from my sample to examine the *extradyadic* patterns of group-based misconduct. As officers are assigned to formal partnerships, looking beyond the dyadic relationship may help mitigate the likelihood that such relationships are mere reflections of the formal structure. Finally, I utilized a more conservative measure of tie strength and only include ties whose weight is greater than two. This allowed me to remove any "one-off" partnerships that, similar to isolates, are more likely to reflect random behavior than a more meaningful relationship among officers. Having executed these steps, I then re-ran the Louvain algorithm to detect the community structure and identify specific communities in each year to trace their evolution over time. My final sample consisted of 8,983 unique officers with 11,756 unique complaints of severe misconduct filed against them (35,450 unique officer-year observations), organized into 6,406 unique communities. I located on average 256 communities per year, the average size of which was 16 officers (ranging from 3 – 150). The average number of complaints per officer is 17; the average number of officers per complaint is 7. Officers tend to share repeat co-complaints three times, on average, and tend to share complaints with 33 other officers over the sample period. My sample is representative of officers who did not receive any complaints during this period in terms of race, gender, and unit assignment, in that they were largely white (60%), male (91%), and assigned to one of the 25 geography-based units rather than assigned to a specialized task force, whose day-to-day duties may differ (57%). **Figure 2** illustrates the community structure of my final sample in 2000. **Table 2** shows summary statistics for the final sample. **Table 3** shows summary statistics for the number and size of communities over time.

Dependent variable: Community longevity

To define and measure community longevity, I build on Simmel's (1898) conceptualization that a social group's persistence reflects some membership continuity in contiguous stages. Previous work generally considers longevity as sharing a certain number of members between time *t* and time *t+1* in order to consider a group as having continued over that time period (Baker, Faulkner, & Fisher, 1998; Vedres & Stark, 2010). Recent scholarship has used a 30% shared membership threshold among partnerships in the global computer industry (Sytch & Tatarynowicz, 2014) or a 50% shared membership continuity model in the Canadian investment bank industry (Rowley et al., 2005). Vedres and Stark (2010) assert that a group must maintain at least two members to be considered continued in the context of entrepreneurship enterprises.

An established measure of community longevity is absent from the wrongdoing literature, and importing such a measure within the context of misconduct communities is problematic. It is likely that network data comprised of misconduct relationships is incomplete due to the difficult nature of getting complete information in these settings (Baker & Faulkner, 1993; Morselli, 2009; Zhang & King, 2021). Indeed, in my context "the blue wall of silence" and the closed nature of policing (Christopher, 1991; Mollen et al., 1994; Weisburd & Greenspan, 2000) make discovering police misconduct – much less attempting to studying it – incredibly difficult (Skogan, 2015). Additionally, police officers may not engage in misconduct together (or be reported for it) every year; as a result, establishing some kind of contiguous longevity measure may miss real relationships that manifest more sporadically over time.

Despite these challenges, establishing an empirical measure for longevity remains crucial, as research demonstrates the increased risk of harm and damage to firms and other stakeholders the longer misconduct continues (Bertrand & Lumineau, 2016). Thus, I retain the general spirit of recent work and measure community longevity via several different measures as a starting point for understanding longevity in context of misconduct. I do so by capturing shared membership thresholds in ten percent increments from 10% – 50% to establish whether a group that existed in time *t* still existed in time *t+1*.

In addition to selecting an appropriate shared membership threshold, an open question also remains as to the best way to calculate that threshold. I leverage Vedres and Stark's (2010) approach, which establishes the number of shared members between a group in time *t* ($G_{i,t}$) and in time *t+1* ($G_{j,t+1}$) as a proportion of the members from $G_{i,t}$. This method captures the extent to which the shared membership between communities is a reflection of the group at time *t* continuing into time *t+1*. For example, if a community had 20 members in time *t*, and ten of those members were also present in a community together in time *t+1*, that would be considered

50% membership continuity and the community would be considered as having "continued." Below I demonstrate this model formally.

$$MembershipOverlap_i = \frac{G_{i,t} \cap G_{j,t+1}}{G_{i,t1}} \qquad \textit{(Dependent Variable)}$$

Using these metrics, I consider $C_{i,t}$ and $C_{j,t+1}$ as a single dynamic group if the percent of shared members was greater than 10%, 20% 30%, 40%, and 50%. If the criteria as indicated in these definitions were met in a given year, I assigned the community a 1 for continuity, and assigned a 0 if otherwise. Across these definitions and shared membership thresholds, community longevity ranges from 1 to 10 years, with the average number of years ranging from one to three years depending on the threshold. Analyzing each of these separate measures of community duration allows me to include robustness with my findings, given the lack of theoretical grounding for membership thresholds within the context of misconduct network communities.

Independent variables

Social Cohesion: Density. To test the effect of overall social cohesion on community longevity, I constructed measures for density. Density measures the actual number of ties among members within-community (T_i) relative to the total number of possible ties among members (*n(n-1)/2*):

$$Density_i = \frac{T_i}{n(n-1)/2}$$

Each community has a value for density in each of the years that it existed. As my data is cross-sectional, I took the mean of density across all years that the community existed to run my regression analyses. In line with Hypothesis 1, I specified both linear and squared effects for this predictor (Haans, Pieters, & He, 2016; Sytch & Tatarynowicz, 2014). I also constructed a measure for density at the time of community founding and determined that my results were robust whether I used the mean value or founding value of density, as community density remained relatively stable over the course of a community's lifetime.

Structural Inequality: Centralization. To test the role of structural inequality on community longevity, I calculate measures of degree point centrality and graph centralization following Freeman (1978, 2014). Centralization measures the extent to which the ties of a given network are concentrated on a single actor or group of actors, or are instead more diffuse and equally distributed among actors. This measure of centralization is based on normalized variance in node centrality, which allows me to measure the relative importance of any given node in a community and then index the tendency of a community to gravitate towards a single (or few) node(s) than all others in the community. To do this, I first calculated the total number of ties per member per community to get a measure of off member icer degree centrality ($C_x(p_i)$) and calculated the largest value of officer member centrality per community ($C_x(p^*)$). Next, I summed the difference between the maximum degree centrality and each node's centrality and divided it by the maximum possible sum of differences in centrality. While negatively correlative with community density, centralization sheds light not on the overall cohesion of the community but specifically the *distribution* of those relationships, capturing the extent to which this distribution is equal or unequal. Formally:

$$Centralization_i = \frac{\Sigma(C_x(p^*) - C_x(p_i))}{\max\Sigma(C_x(p^*) - C_x(p_i)}$$

Each community has a value for centralization in each of the years that it existed. As my data is cross-sectional, I took the mean of centralization across all years that the community existed to run my regression analyses. In line with Hypothesis 2, I specified both linear and squared effects for this predictor (Haans et al., 2016; Sytch & Tatarynowicz, 2014). I also constructed a measure for centralization at the time of community founding and determined that my results were robust whether I used the mean value or founding value of centralization, as community centralization remained relatively stable over the course of a community's lifetime.

Control variables

I ran my analyses controlling separately for both community size and logged community size, as these measures correlate with both density and centralization. I used a logged measure given the wide variance of community sizes, but my results were robust to using either measure of community size (logged or not). Also, as I included squared terms for my independent variables, I also included a squared term for community size; my results were robust whether I included a squared term or not. Next, I included founding-year fixed effects to control for any heterogeneity that might exist due to the year at which a community started. For example, changes in police accountability structures, public opinion and the political viewpoints of those in office may all effect the extent to which police misconduct occurs and / or is reported (Kalven, 2016; Taylor, 2012). I also controlled for several community demographic characteristics, including percent white, percent male, unit, complaint type, unit diversity – that is, the number of different units represented in a community – as well as complaint diversity – that is, the number of different types of complaints comprised in a community. These last four controls in particular can help mitigate issues arising from the formal structure of the organization, as well as omitted variable bias related to type of misconduct.

Finally, exploring longevity as a dependent variable can raise questions regarding censoring of the data. When studying duration, data censoring can arise if the community either continues after the sample concludes ("right-censoring") or if the community existed before the sample began ("left-censoring") (Lagakos, 1979). Right-censorship is more common (Leung, Elashoff, & Afifi, 1997) and presents a possibility of selection bias that can bias inference regarding the survival time distribution (Andersen, 2014). To assess the extent to which right-censorship may be an issue in my data, I first confirm that over 99% of communities in my sample expired before the end of the sample itself. Thus, I do not expect right-censoring to skew my results. Nonetheless, I included a dummy variable as to whether the community died during the sample's timeframe, as not all communities had died by the end of 2015 and community death correlates negatively with community longevity. Regarding possible left-censorship, I confirm that 4.68% of communities started in 1991, the beginning of my sample. Importantly, I did not find a statistically significant network community structure before 1991, per Newman and colleagues (Newman, 2006, 2011, 2016); thus, empirically there is not sufficient community structure to analyze prior to 1991. Similar to prior work on longevity (see Baker et al., 1998; Bertrand and Lumineau, 2016), I therefore do not expect selection bias related to left-censorship in my models, though the inclusion of fixed effects for year of founding helps control for any time-based selection bias, as indicated previously. **Table 4A** notes summary statistics for my dependent, independent, and control variables; **Table 4B** notes correlation matrices for these measures. **Figure 3** depicts a graph of the relationship between my measures of social cohesion and structural inequality, as they correlate highly negatively.

Finally, I execute an ordinary least squares regression using fixed effects and robust standard errors in STATA S/E 17.0[5]. As my independent variables are highly negatively

[5] With cross-sectional data and a count variable as a dependent variable, either a traditional OLS regression or a Poisson regression would be appropriate (Coleman, 1964). Poisson regression models the number of occurrences of an event and calculates an incidence rate ratio to calculate the relative incidence rate of the dependent variable as the independent variable(s) change (Chatterjee & Hadi, 2006). I follow work from Gaure (2011) and Guimarães and Portugal (2010) and execute my models using OLS, as interpreting curvilinear effects with Poisson can be challenging (Coxe et al., 2009); however, I also run the analyses using Poisson and the results are robust to either method. Additionally, a Cox proportional hazards model could be appropriate as it models the relationship between covariates and risk of failure (Kleinbaum & Klein, 2012), which is a slightly different way of conceptualizing my research question. Cox models can be used for count data, but these models often do not perform as well as other models (such as OLS or Poisson) and can make interpretation difficult when modeling data with non-normal distributions (Lin & Wei, 1989), as is the case with my dataset. Nevertheless, I also run a Cox model and find the

correlative, I run my models to assess each relationship independent of each other, rather than a model that includes them both together. As they are both co-determined and thus multicollinear, including them together in the same model would likely produce incorrect results (Schroeder, Lander, & Levine-Silverman, 1990; Farrar & Glauber, 1964)[6].

RESULTS

Tables **5A and 5B** reveal results for all models at the 10 – 50% membership thresholds controlling for community death and community size (actual), with yearly fixed effects. Results are robust when using logged community size instead of community size (actual). The results from my models indicate support for Hypothesis 1 at all membership thresholds. Following guidance from Haans and colleagues (2016), I adhere to the following steps to confirm that my hypothesized curvilinear effects do, indeed, hold true. The first is that the first-order linear term for the independent variable must be included in the regression (Aiken, West, & Reno, 1991). A significant and negative squared term indicates the inverted U-shaped relationship that I hypothesized in H1: community density is first associated with increased community longevity, but eventually it reaches a tipping point and becomes associated with *decreased* community longevity. However, though necessary, a significant squared term alone is not sufficient to establish a quadratic relationship (Lind & Mehlum, 2010). The slope needs to be sufficiently steep at both ends of the data range. In **Table 6A** I calculate the margins at several points along the density distribution to show that the slope is significant at the 95% confidence interval.

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results are robust to any of the three modeling approaches, including survival analysis. Please refer to **Appendix A** for Cox model results.

[6] In an effort to mitigate multicollinearity, I also ran my analyses using number of structural holes as a measure of community fragmentation. Number of structural holes has been demonstrated to capture structural inequality within a community and can reflect fragmentation, which leads to an uneven exertion of normative constraints (Rowley, Greve, Rao, Baum, & Shipilov, 2005; Burt, 1992b; Borgatti, Everett, & Freeman, 1999). Results were robust to either measure of structural inequality; please refer to **Appendix B** for results.

Figures 4 – 8 depict graphically these margins plots and show that the turning point is located well within my data range. Taken together, these results suggest that overall, community density does exert a curvilinear effect on community longevity and thus Hypothesis 1 is supported at all membership threshold models.

Next, the results from my models also indicate support for Hypothesis 2 across all membership threshold specifications. I replicate my steps from H1 based on Haans and colleagues (2016) to confirm that my hypothesized curvilinear effects do, indeed, hold true. The first is that the first-order linear term for the independent variable must be included in the regression (Aiken et al., 1991). A significant and negative squared term indicates the inverted U-shaped relationship that I hypothesized in H2: community centralization is first associated with increased community longevity, but eventually it reaches a tipping point and becomes associated with *decreased* community longevity. Again, a significant squared term is not sufficient to establish a quadratic relationship (Lind & Mehlum, 2010), and so I thus confirm that the slope is sufficiently steep at both ends of the data. In **Table 6B** I calculate the margins at several points along the centralization distribution to show that the slope is significant at the 95% confidence interval. **Figures 9 – 12** depict graphically these margins plots and show that the turning point is located well within my data range. Taken together, these results suggest that overall, community centralization does exert a curvilinear effect on community longevity and thus Hypothesis 2 is supported at all membership threshold models.

DISCUSSION

Misconduct is a reality of organizational life and has enormous consequences for firms and society (Greve, Palmer, et al., 2010; Palmer, 2012; Palmer et al., 2016). In the US economy alone, it is estimated that 13% of firms engage in fraud and that such wrongdoing costs somewhere between $180 to $360 billion annually (Dyck, Morse, & Zingales, 2021). Most extant research explores the antecedents of misconduct at the individual or organizational levels. This work is valuable, but recent research indicates that wrongdoing is often a coordinated action involving more than one individual (Aven, 2015; Palmer & Yenkey, 2015), and there have been calls to explore this phenomenon through a social network lens (Palmer & Moore, 2016). Unfortunately, doing so poses enormous challenges to researchers as the reality of data (un)availability generally impedes such work (Wang et al., 2021). This study is one attempt to uncover patterns of organized misconduct with a unique longitudinal dataset and thus contribute to our understanding of organizational wrongdoing as an organized phenomenon.

This study investigates the role of two key structural characteristics on the persistence of misconduct communities: social cohesion and structural inequality. I take a network community approach and locate communities of police officers embedded within the broader Chicago Police Department who are engaging in misconduct activities together. Little is known about misconduct as a structural, organized phenomenon among many actors that evolves over time (Palmer & Moore, 2016). I offer a novel theoretical framework in which the persistence of community-based misconduct is a function not just of its overall social cohesion (its density) but also of the specific distribution of that cohesion (its centralization). I define community longevity as the number of contiguous years that a community maintains certain levels of membership. Using longitudinal data from the CPD 1991 – 2015, I find overall support for my hypotheses that social cohesion and structural inequality have inverted curvilinear relationships on community longevity. Taken together, this study expands our understanding of the structural underpinnings of how organized misconduct may persist over time.

In this study I define communities as significant meso-level structures between dyads and networks, whose interconnections are denser than in other regions of the network and thus create a pattern of tie formation that engenders relatively cohesive local structures (Thornton, Ocasio, & Lounsbury, 2012; Newman, 2016). Importing work that explore communities as institutional logics (Marquis & Battilana, 2009), I assert that misconduct communities embody regional social contexts with their own norms and monitoring capabilities, and that as such they are a meaningful driver of the persistence of misconduct. While communities are, by nature, more cohesive than other areas of a network, that cohesiveness still varies dramatically based on community structure (Marquis et al., 2007). In this study, I specifically explore the role of two types of social cohesion: density, or a community's overall level of social cohesion, which captures the amount of closure among within-community relationships, and centralization, which captures the specific tie distribution structure of a community and captures the extent to which this distribution is equal or unequal among community members. I argue that both of these constructs influence the extent to which communities can enforce norms, monitor the behavior of members, and fly under the radar of would-be interlopers, and that the ability to do so has implications for how long a misconduct community persists.

I hypothesized that density would be initially helpful for a community in this setting as it promotes norm strength and strong monitoring capabilities among members (Coleman, 1988; Granovetter, 1985), but would eventually become a liability, as denser communities are easier to disrupt that sparser ones (Baker & Faulkner, 2009; Everton & Cunningham, 2015; Morselli et al., 2007; Simmel, 1906). My results support this hypothesis across all specified membership thresholds. I next hypothesized that centralization would initially be positive for community longevity as it improves efficiency while lowering the risk of outsider detection, but that it would eventually become more difficult to operate as a unified group (S. F. Everton & Cunningham, 2015; Morselli et al., 2007), as the normative strength of the community would be weakened and the risk of member attrition would thus be higher (Shapiro, 2013; Greve, Baum, et al., 2010; Rowley et al., 2005). My findings support these relationships and, taken together, suggest that these communities do operate as their own form of institutional environments and that moderate levels of density and centralization may best suit such communities' ongoing longevity.

There are a few limitations to this study that warrant mention. The first relates to the difficulty of acquiring complete network data, especially in a "dark" context in which secrecy is inherent (Wang et al., 2021). Given the nature of the phenomenon I am studying, it is difficult to confirm that my dataset indeed reflects all acts of actual wrongdoing among police officers. This is a common problem among most research that attempts to study misconduct (Baker & Faulkner, 1993; Cunningham et al., 2016; Morselli, 2009), but it nevertheless needs to be noted. It is possible that I have missed key acts of misconduct that were systematically unreported due to intimidation or power imbalances between perpetrators and victims (Ba, 2018); these shortcomings have been well-documented in prior work, and it is possible that they apply to my sample as well. Conversely, it is possible that my data is skewed by formal organizational structures, such as partner and unit assignments, that influence likelihood of receiving complaints. Following recent work by Jain and colleagues (2022) I have made a number of sampling decisions that maximize the likelihood of this data capturing real misconduct relationships, but this risk is still a possibility in my data.

Relatedly, an alternative explanation for the findings in my data is that only the particularly dysfunctional communities are "caught" (via complaints) and that there are actually communities who, as density and / or centralization grow, become more functional and become better at conducting their business. If this were the case, the results showing the inverted curvilinear effect would in fact be missing the *linear* relationship such that as density / centralization increases, longevity increases as well. There are a few reasons to cast doubt on this possibility. First, as much research on so-called "dark" networks has demonstrated, even fully-illicit organizations such as drug rings (Bouchard, 2007; Calderoni, 2012), terrorist groups (Asal & Rethemeyer, 2008) or the Mafia (Agreste, Catanese, De Meo, Ferrara, & Fiumara, 2016; DellaPosta, 2017) navigate tensions between social cohesion and structural inequality and often face repercussions for becoming too dense or too centralized. Thus, even in cases where such network structures have the highest incentive to remain as secret as possible, the tradeoffs I describe in my theorizing still apply. Additionally, network research demonstrates that most often, network community members have very little insight into the overall structure within which they are embedded (Burt, 2002; Friedkin, 1983). Thus, while members might have some understanding of how they fit structurally with their direct ties, a broader sense of community properties is likely to be very limited. Together, this suggests that the curvilinear effects demonstrated in this context are not likely to be missing a core quadrant of communities who simply become more intentional or better at hiding their behaviors; however, it is still a possibility that the "darkest" of network communities remain entirely off the grid and that, as such, we do not ever – or only are partially – aware of their behaviors over time (Milward, 2015).

Next, given the paucity of research on organized misconduct, there is very little existing guidance on establishing empirical measures of continuity. This paper represents one attempt to define misconduct persistence as based on shared membership over contiguous years. I define shared membership as a percent of the community in year *t* and specify membership thresholds at the 10 – 50% levels. I expect my results are more conservative in part due to this contiguous definition; future work may benefit from exploring broader time specifications to see if communities may persist (i.e., four-year windows; see Rowley et al., 2005). My findings suggest that the membership thresholds do not meaningfully change the effect of my independent variables on community survival. While this method is inspired by prior work in sociology (Vedres & Stark, 2010) and in organizational management research (Greve, Baum, et al., 2010; Rowley et al., 2005; Sytch & Tatarynowicz, 2014), it nonetheless is a first attempt to bring such measures into the context of misconduct. As such, this topic would benefit greatly from future work exploring and testing theoretical justifications for particular empirical measures of misconduct persistence.

Lastly, this study takes place in the Chicago Police Department, a context notorious for its corruption and misconduct (Gonzalez van Cleve, 2016; Kalven, 2016; US Department of Justice, 2017). While I argue this makes it a particularly compelling context to examine the structural underpinnings of the persistence of organized misconduct, my results may be somewhat limited in generalizability. Indeed, it is possible that the somewhat-normalized nature of misconduct has helped such behavior be seen as more “business as usual” rather than a dire problem for the organization, and may influence the extent to which these groups make tradeoffs regarding security versus efficiency: “security” may just not be much of a risk here, as fewer than four percent of officers accused of misconduct experience any form of punishment (Invisible Institute, 2018). Future work should explore these dynamics in other contexts in which misconduct may be rarer, as misconduct communities embedded in such settings may make different choices when attempting to balance group coordination, cohesiveness, and security. For example, in the context of most legitimized business environments, the threshold of tolerance for misconduct may be much lower and the concern of buffering outsider threats may be much higher. At the same time, recent headlines indicate that many top companies and institutions are plagued by such misconduct "cells" – these pockets of actors engaging in misconduct – and many have paid heavy financial and reputational prices for such behavior within their midst. Exploration on this topic in different organizational contexts would improve the robustness of this paper's theoretical framework and further generalize its findings.

CONCLUSION

Organizational misconduct is an incredibly diverse phenomenon. Much scholarly work has explored different manifestations of this concept, ranging from individual perpetrators, to permissive or corrupt organizational contexts, to pockets of actors embedded within environments hostile to – or misaligned with – their behaviors. Research explores misconduct done in the perpetrator's own interest or on behalf of the organization. While this is an incredibly rich body of work, there is more work to be done regarding misconduct as an *organized* phenomenon comprised of multiple actors. This paper helps push forward in addressing this gap.

Exploring the structural attributes of groups engaging misconduct is a step towards understanding the fundamental question: "how do they get away with it for so long?" In considering misconduct as a relational phenomenon, it behooves us to consider the relational aspects of these groups that contribute to their success in managing the tensions between security and efficiency over time. Some groups seem to clearly be better than others at perpetuating misconduct while mitigating outsider interference. In proposing a community-based theory of misconduct, I offer clear patterns that can help policy and organizational leaders better anticipate and interrupt organized misconduct by leveraging network data to identify these patterns. My findings suggest that more cohesion and less structural equality best positions these groups to survive over time. While we tend to consider misconduct as a phenomenon of bad apples, or of bad barrel cultures, my findings indicate that actually there are relational structures that reflect coordination patterns and establish pockets somewhere between the bad apple and bad barrel analyses. Thus, this paper contributes to organizational research by offering a novel theory of the persistence of misconduct over time and sets the groundwork for future research to further test and refine its findings.

FIGURES

Figure 3.1. Network structure of CPD global network (all severe complaints), 2000.
Note: Red dots are officers; links are co-complaints they have in common.

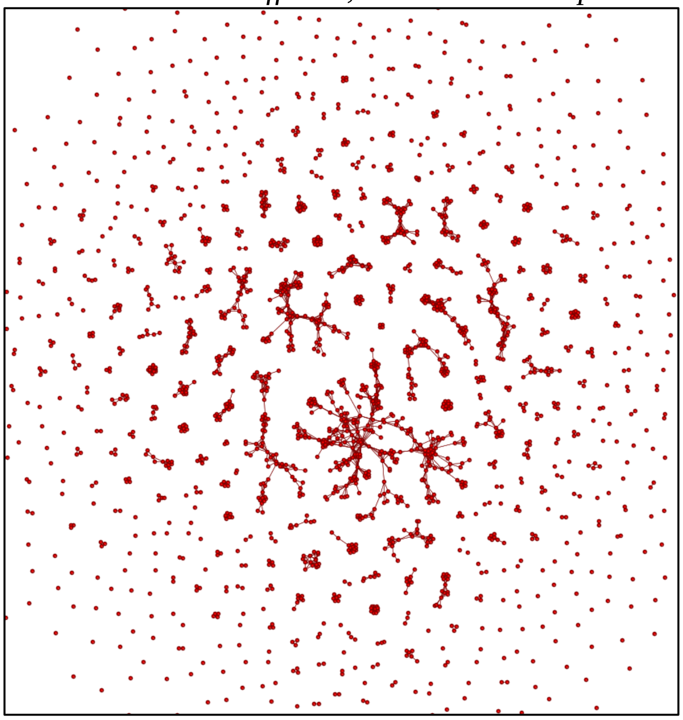


Figure 3.2. Network community structure of final CPD sample, 2000.
Note: Red dots are officers; links are co-complaints they have in common.

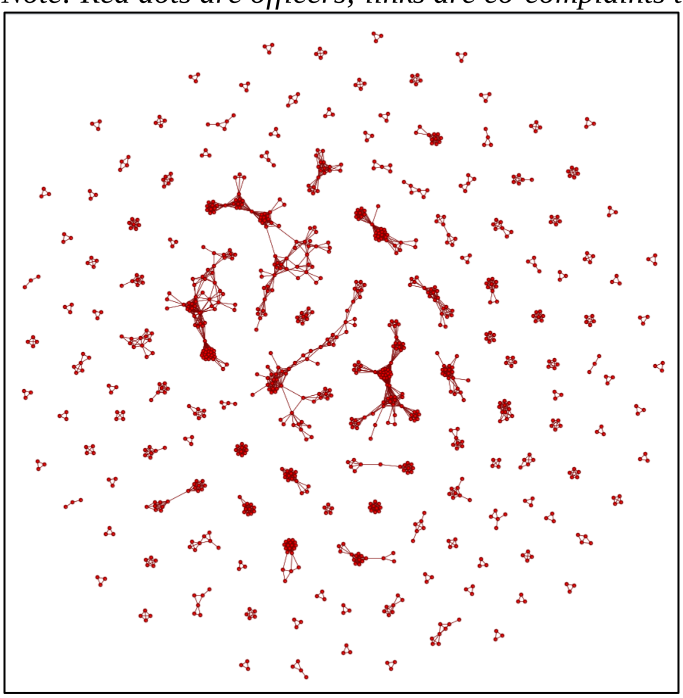


Figure 3.3. Relationship between community density and centralization.
X axis: community centralization; Y axis, community density

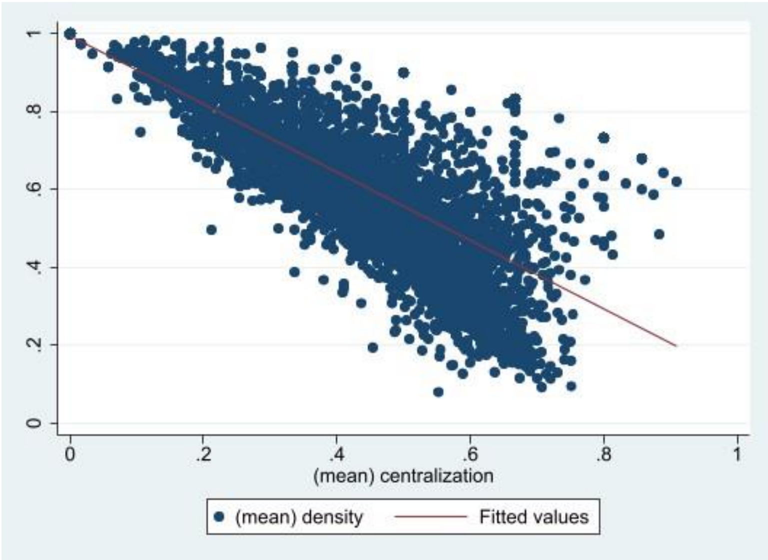


Figure 3.4. Relationship between community density and longevity, threshold 10%.
X axis: community density; Y axis: average community duration.

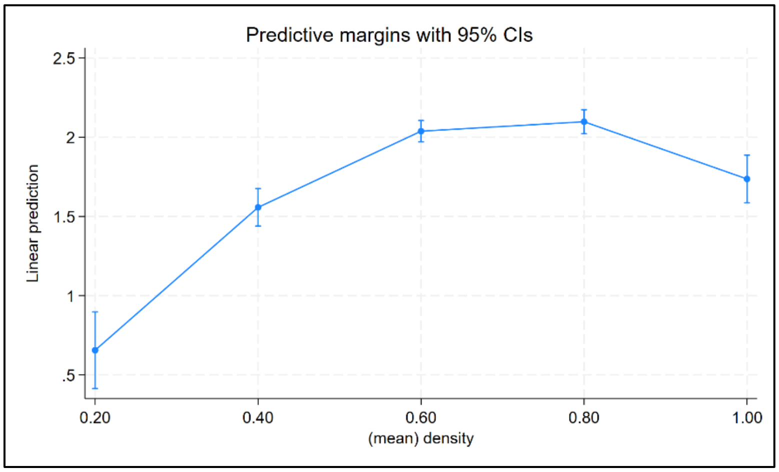


Figure 3.5. Relationship between community density and longevity, threshold 20%.
X axis: community density; Y axis: average community duration.

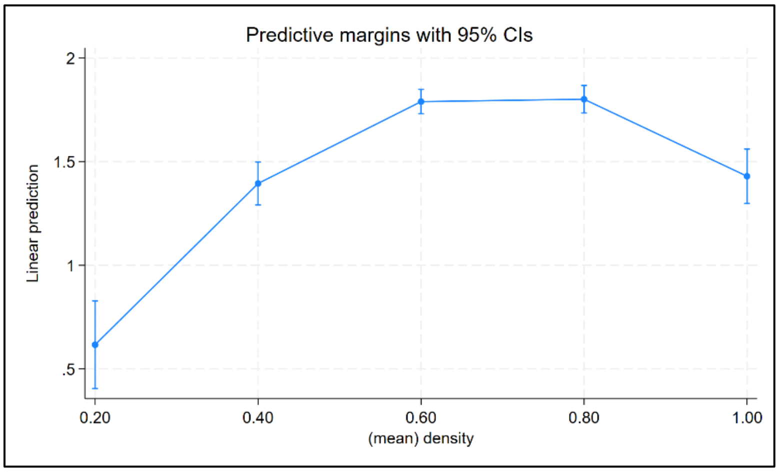


Figure 3.6. Relationship between community density and longevity, threshold 30%.
X axis: community density; Y axis: average community duration.

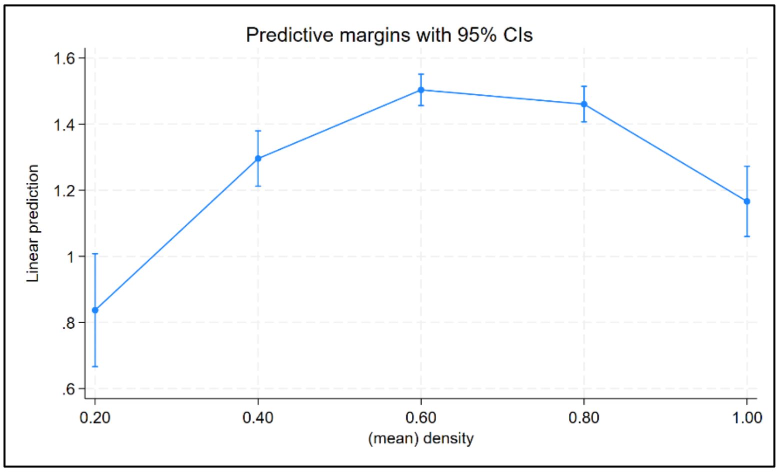


Figure 3.7. Relationship between community density and longevity, threshold 40%.
X axis: community density; Y axis: average community duration.

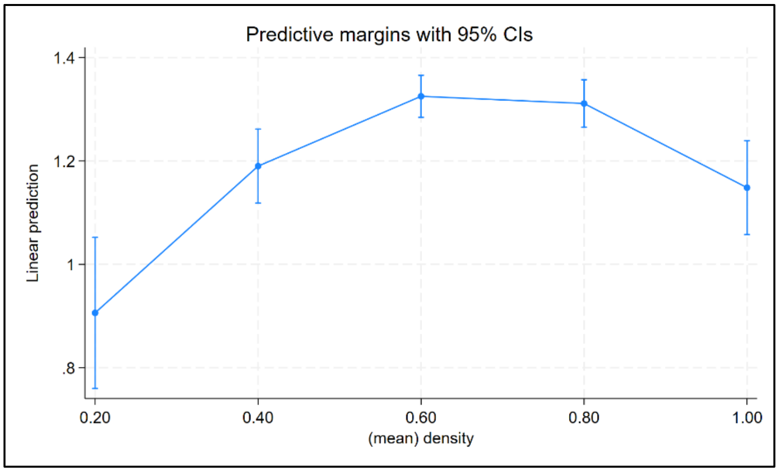


Figure 3.8. Relationship between community density and longevity, threshold 50%.
X axis: community density; Y axis: average community duration.

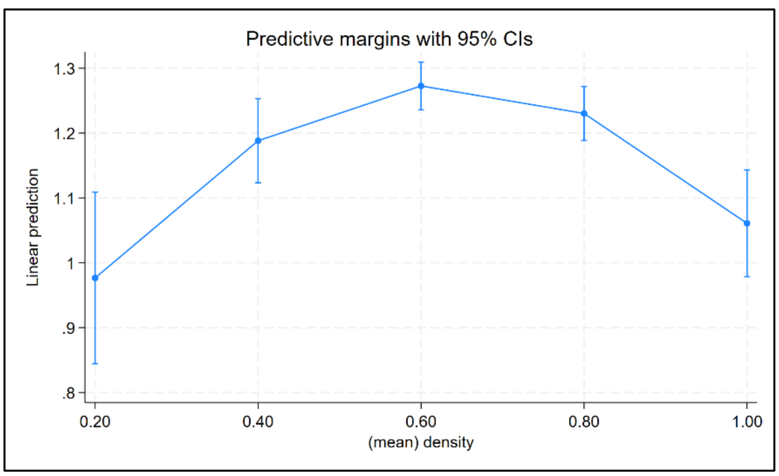


Figure 3.9. Relationship between community centralization and longevity, threshold 10%.
X axis: community centralization; Y axis: average community duration.

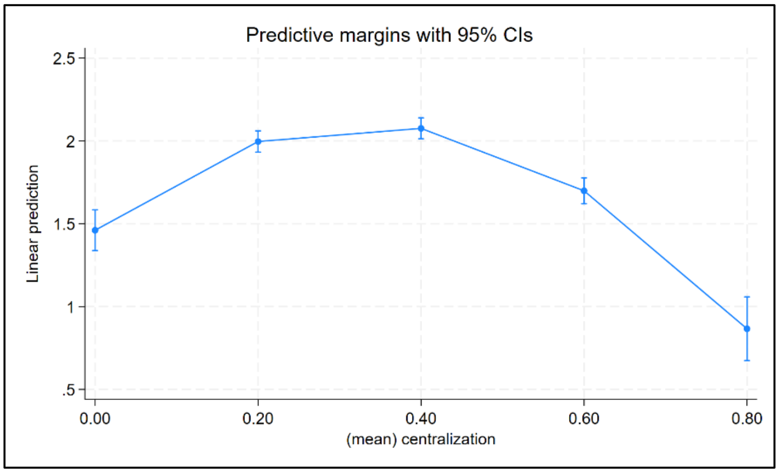


Figure 3.10. Relationship between community centralization and longevity, threshold 20%.
X axis: community centralization; Y axis: average community duration.

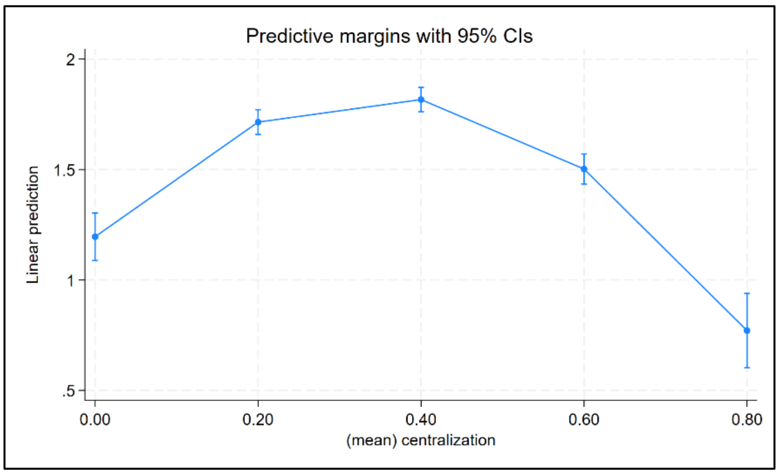


Figure 3.11. Relationship between community centralization and longevity, threshold 30%.
X axis: community centralization; Y axis: average community duration.

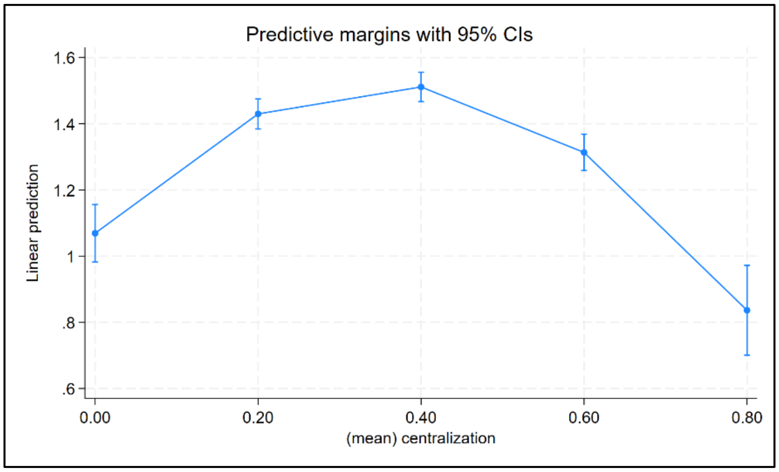


Figure 3.12. Relationship between community centralization and longevity, threshold 40%.
X axis: community centralization; Y axis: average community duration.

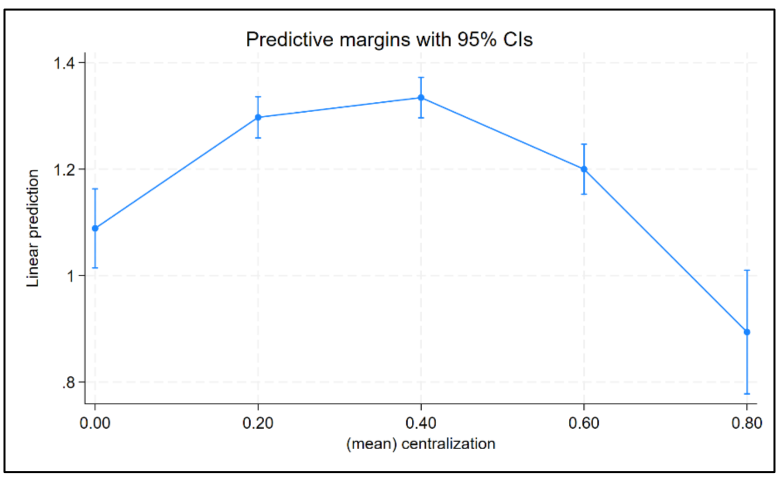
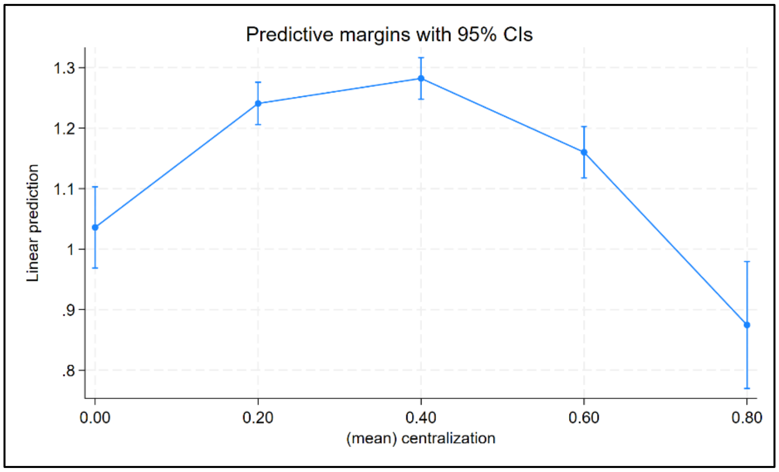


Figure 3.13. Relationship between community centralization and longevity, threshold 50%.
X axis: community centralization; Y axis: average community duration.



TABLES

Table 3.1. Summary statistics for all severe complaints 1991 – 2015 (global population).

Variable	Observations	Mean	Std	Min	Max
Severe complaint categories					
Improper arrest	58,030	0.51	0.50	0	1
Excessive force	58,030	0.33	0.47	0	1
Illegal search	58,030	0.26	0.44	0	1
Civil rights violations	58,030	0.20	0.40	0	1
Bribery	58,030	0.04	0.20	0	1
Criminal misconduct	58,030	0.04	0.20	0	1
Racial profiling	58,030	0.02	0.15	0	1
Sexual misconduct	58,030	0.00	0.06	0	1
Severe complaints filed by officers	58,030	0.01	0.12	0	1
Officer race *(white)*	12,997	0.52	0.50	0	1
Officer gender *(male)*	12,997	0.74	0.43	0	1
Officer unit assignment *(geographic)*	12,997	0.53	0.50	0	1
Community size	25,496	2.60	0.60	1	188
Newman modularity	25	0.94	0.07	0.61	0.98

Table 3.2. Summary statistics for final sample, 1991 – 2015.

Variable	Observations	Mean	Std	Min	Max
Officers per complaint	35,450	7.22	15.27	2	188
Complaints per officer	35,450	17.01	14.36	2	116
Tie strength between officers	35,450	2.88	2.79	1	39
Overall ties per officer	35,450	33.34	79.28	2	2,112
Complaints per community	35,450	15.51	18.67	1	100
Complaint variability per community	35,450	3.74	1.58	1	7
Unit variability per community	35,450	12	10	1	54
Severe complaint categories					
Improper arrest	11,756	0.50	0.50	0	1
Excessive force	11,756	0.30	0.46	0	1
Illegal search	11,756	0.35	0.48	0	1
Civil rights violations	11,756	0.26	0.44	0	1
Bribery	11,756	0.01	0.11	0	1
Criminal misconduct	11,756	0.03	0.18	0	1
Racial profiling	11,756	0.01	0.12	0	1
Sexual misconduct	11,756	0.00	0.03	0	1
Severe complaints filed by officers	11,756	0.01	0.09	0	1
Officer race *(white)*	8,983	0.60	0.49	0	1
Officer gender *male)*	8,983	0.91	0.29	0	1
Officer unit assignment *(geographic)*	8,983	0.57	0.50	0	1
Newman modularity	25	0.93	0.07	0.59	0.97
Community size	6,460	16.25	20.50	3	150
Community percent white	6,460	0.60	0.35	0	1
Community percent male	6,460	0.90	0.19	0	1
Year	6,460	2000	6.15	1991	2015

Table 3.3. Final sample communities, officers, and complaints 1991 – 2015.

Year	Communities	Officers	Complaints
1991	300	746	784
1992	255	327	417
1993	294	425	485
1994	343	524	708
1995	403	430	639
1996	431	600	887
1997	408	592	844
1998	385	375	513
1999	345	451	634
2000	349	381	609
2001	333	325	625
2002	325	361	711
2003	269	333	534
2004	214	278	452
2005	226	230	309
2006	249	347	430
2007	227	379	402
2008	217	328	295
2009	205	362	367
2010	153	262	285
2011	138	259	224
2012	116	186	200
2013	106	214	171
2014	79	181	158
2015	36	87	73
Total	**6,406**	**8,983**	**11,756**
Average	256.24	359.32	470.24

Table 3.4A. Summary statistics for dependent, independent, and control variables.

Variable	Obs	Mean	Med	Std.	Min	Max
(1) Community density	6,457	0.71	0.71	0.24	0.08	1.00
(2) Community centralization	6,457	0.32	0.35	0.24	0.00	0.91
(3) Community structural holes	6,457	1.98	1.68	1.18	1.00	19
(4) Community size	6,457	15.60	11	13.56	3.00	150
(5) Community size *(logged)*	6,457	2.24	2.25	0.79	1.10	5.01
(6) Community percent white	6,457	0.62	0.67	0.28	0.00	1.00
(7) Community percent male	6,457	0.92	0.96	0.13	0.00	1.00
(8) Mode complaint type per community	3,894	1.98	2	1.15	1.00	8.00
(9) Mode unit type per community	5,306	189	20	228	1	765
(10) Complaint variability per community	6,457	3.74	4	1.58	1	7
(11) Unit variability per community	6,457	12	9	10.36	1	54
(12) Community density *(at found)*	6,457	0.71	0.8	0.30	0.08	1.00
(13) Community centralization *(at found)*	6,457	0.32	0.4	0.28	0.00	0.91
(14) Community structural holes *(at found)*	6,457	1.98	1.22	1.59	1.00	18.50
(15) Community died *(dummy)*	6,421	0.99	1	0.08	0.00	1.00
(16) Year	6,457	2000	2000	6	1991	2015
(17) Community duration						
10% membership	6,457	1.82	1	1.32	1	10
20% membership	6,457	1.59	1	1.18	1	10
30% membership	6,457	1.39	1	1.02	1	10
40% membership	6,457	1.26	1	0.85	1	10
50% membership	6,457	1.21	1	0.77	1	10

Table 3.4B. Correlation matrix for dependent, independent, and control variables.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	1.0000														
(2)	-0.868***	1.0000													
(3)	-0.668***	0.506***	1.0000												
(4)	-0.793***	0.570***	0.794***	1.0000											
(5)	-0.891***	0.695***	0.791***	0.893***	1.0000										
(6)	-0.048***	0.028**	0.008	0.021*	0.033***	1.0000									
(7)	-0.072***	0.090***	0.021*	0.037***	0.050***	0.061***	1.0000								
(8)	0.032**	-0.055***	-0.006	-0.034**	-0.002	0.040**	-0.068***	1.0000							
(9)	-0.015	0.005	-0.030**	-0.014	-0.006	0.053***	0.030**	0.017	1.0000						
(10)	0.810***	-0.701***	-0.529***	-0.651***	-0.723***	-0.026**	-0.067***	0.064***	-0.011	1.0000					
(11)	-0.731***	0.841***	0.412***	0.474***	0.582***	0.009	0.086***	-0.084***	0.005	-0.859***	1.0000				
(12)	-0.466***	0.353***	0.772***	0.623***	0.584***	-0.029**	0.015	-0.046***	-0.036***	-0.587***	0.434***	1.0000			
(13)	-0.023*	0.01	0.030**	0.023*	-0.001	0.031**	-0.022*	0.045***	0.038***	-0.015	0.011	0.015	1.0000		
(14)	0.241***	-0.207***	-0.046***	-0.192***	-0.135***	0.007	-0.001	-0.002	-0.132***	0.198***	-0.171***	-0.062***	-0.173***	1.0000	
(15)	-0.423***	0.332***	0.351***	0.398***	0.440***	0.041***	0.067***	0.018	0.027*	-0.335***	0.270***	0.223***	-0.053***	-0.150***	1.0000

**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Table 3.5A. Results at shared membership thresholds 10 – 30%.

VARIABLES	10%				20%				30%			
Density	**0.650*** **	**7.667*** **			**0.378** **	**6.766*** **			-0.00654	**4.176*** **		
	(0.216)	(0.628)			(0.189)	(0.550)			(0.152)	(0.444)		
Density squared		-5.263***				-4.792***				**-3.137*** **		
		(0.444)				(0.388)				(0.314)		
Centralization			-0.161	**3.820*** **			0.00143	**3.638*** **			0.0660	**2.502*** **
			(0.141)	(0.368)			(0.124)	(0.322)			(0.0990)	(0.260)
Centralization squared				**-5.705*** **				**-5.211*** **				**-3.491*** **
				(0.489)				(0.427)				(0.345)
Community size	0.0822***	0.0835***	0.0714***	0.0626***	0.0690***	0.0702***	0.0614***	0.0534***	0.0489***	0.0497***	0.0481***	0.0428***
	(0.00633)	(0.00619)	(0.00502)	(0.00498)	(0.00554)	(0.00542)	(0.00440)	(0.00435)	(0.00445)	(0.00438)	(0.00352)	(0.00351)
Community size squared	-0.000663***	-0.000510***	-0.000602***	-0.000451***	-0.000545***	-0.000406***	-0.000501***	-0.000363***	-0.000392***	-0.000301***	-0.000387***	-0.000295***
	(6.59e-05)	(6.58e-05)	(6.24e-05)	(6.24e-05)	(5.78e-05)	(5.75e-05)	(5.46e-05)	(5.46e-05)	(4.63e-05)	(4.65e-05)	(4.38e-05)	(4.40e-05)
Community percent white	0.251***	0.269***	0.238***	0.231***	0.204**	0.221***	0.196**	0.190**	0.153**	0.164***	0.152**	0.148**
	(0.0906)	(0.0887)	(0.0906)	(0.0887)	(0.0794)	(0.0776)	(0.0794)	(0.0776)	(0.0637)	(0.0627)	(0.0636)	(0.0626)
Community percent male	0.322*	0.291*	0.319*	0.293*	0.292*	0.264*	0.289*	0.265*	0.203	0.184	0.201	0.186
	(0.176)	(0.173)	(0.177)	(0.173)	(0.155)	(0.151)	(0.155)	(0.151)	(0.124)	(0.122)	(0.124)	(0.122)
Complaint type	0.0195	0.0415	0.0158	0.0394	-0.00902	0.0110	-0.0130	0.00858	-0.0588	-0.0457	-0.0599	-0.0455
	(0.0774)	(0.0758)	(0.0775)	(0.0759)	(0.0678)	(0.0663)	(0.0679)	(0.0664)	(0.0544)	(0.0536)	(0.0544)	(0.0536)
Unit	0.470**	0.453**	0.464**	0.425**	0.409**	0.394**	0.406**	0.371**	0.204	0.194	0.204	0.181
	(0.209)	(0.204)	(0.209)	(0.205)	(0.183)	(0.179)	(0.183)	(0.179)	(0.147)	(0.145)	(0.147)	(0.144)
Community unit diversity	-0.0272	-0.0262	-0.0212	-0.0214	-0.0329	-0.0320	-0.0302	-0.0304	-0.0271	-0.0265	-0.0277	-0.0279
	(0.124)	(0.121)	(0.124)	(0.122)	(0.109)	(0.106)	(0.109)	(0.106)	(0.0871)	(0.0858)	(0.0871)	(0.0857)
Community complaint diversity	0.0726	-0.0316	0.0659	-0.0453	0.0484	-0.0464	0.0372	-0.0644	0.113*	0.0506	0.108*	0.0397
	(0.0864)	(0.0850)	(0.0869)	(0.0856)	(0.0757)	(0.0743)	(0.0761)	(0.0749)	(0.0607)	(0.0601)	(0.0610)	(0.0604)
Community death *(dummy)*	-1.540***	-1.396***	-1.544***	-1.398***	-1.255***	-1.124***	-1.256***	-1.122***	-0.937***	-0.852***	-0.936***	-0.847***
	(0.237)	(0.232)	(0.237)	(0.232)	(0.207)	(0.203)	(0.208)	(0.203)	(0.166)	(0.164)	(0.166)	(0.164)
Constant	1.225***	-0.748*	1.928***	1.744***	1.447***	-0.349	1.857***	1.688***	1.664***	0.488	1.657***	1.545***
	(0.417)	(0.441)	(0.346)	(0.339)	(0.366)	(0.386)	(0.303)	(0.296)	(0.293)	(0.312)	(0.243)	(0.239)
Observations	3,298	3,298	3,298	3,298	3,298	3,298	3,298	3,298	3,298	3,298	3,298	3,298
R-squared	0.201	0.235	0.199	0.232	0.208	0.245	0.207	0.243	0.212	0.236	0.212	0.237

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.5B. Results at shared membership thresholds 40 & 50%.

VARIABLES	40%				50%			
Density	0.0548	**2.537*** **			-0.106	**2.009*** **		
	(0.129)	(0.380)			(0.117)	(0.344)		
Density squared		**-1.862*** **				-1.587***		
		(0.268)				(0.243)		
Centralization			-0.0243	**1.472*** **			0.00733	**1.433*** **
			(0.0841)	(0.222)			(0.0760)	(0.201)
Centralization squared				**-2.144*** **				**-2.043*** **
				(0.295)				(0.267)
Community size	0.0353***	0.0357***	0.0345***	0.0312***	0.0266***	0.0270***	0.0286***	0.0255***
	(0.00377)	(0.00375)	(0.00299)	(0.00300)	(0.00341)	(0.00339)	(0.00271)	(0.00271)
Community size squared	-0.000267***	-0.000213***	-0.000263***	-0.000206***	-0.000230***	-0.000184***	-0.000241***	-0.000187***
	(3.93e-05)	(3.98e-05)	(3.71e-05)	(3.77e-05)	(3.56e-05)	(3.60e-05)	(3.36e-05)	(3.40e-05)
Community percent white	0.0910*	0.0974*	0.0900*	0.0875	0.0791	0.0846*	0.0814*	0.0791
	(0.0540)	(0.0537)	(0.0540)	(0.0535)	(0.0489)	(0.0486)	(0.0488)	(0.0484)
Community percent male	0.117	0.106	0.117	0.107	0.112	0.102	0.113	0.104
	(0.105)	(0.104)	(0.105)	(0.104)	(0.0951)	(0.0945)	(0.0951)	(0.0942)
Complaint type	-0.0589	-0.0511	-0.0590	-0.0501	-0.0947**	-0.0881**	-0.0937**	-0.0853**
	(0.0462)	(0.0458)	(0.0462)	(0.0458)	(0.0417)	(0.0415)	(0.0418)	(0.0414)
Unit	0.195	0.189	0.194	0.180	0.123	0.118	0.124	0.110
	(0.125)	(0.124)	(0.125)	(0.124)	(0.113)	(0.112)	(0.113)	(0.112)
Community unit diversity	-0.00310	-0.00275	-0.00250	-0.00259	-0.00303	-0.00273	-0.00385	-0.00394
	(0.0740)	(0.0734)	(0.0740)	(0.0734)	(0.0669)	(0.0664)	(0.0669)	(0.0663)
Community complaint diversity	0.0484	0.0116	0.0487	0.00687	-0.00430	-0.0357	-0.00176	-0.0416
	(0.0515)	(0.0514)	(0.0518)	(0.0517)	(0.0466)	(0.0465)	(0.0468)	(0.0467)
Community death *(dummy)*	-0.931***	-0.880***	-0.932***	-0.877***	-0.733***	-0.690***	-0.733***	-0.680***
	(0.141)	(0.140)	(0.141)	(0.140)	(0.128)	(0.127)	(0.128)	(0.127)
Constant	1.616***	0.918***	1.675***	1.606***	1.670***	1.075***	1.555***	1.489***
	(0.249)	(0.267)	(0.206)	(0.205)	(0.225)	(0.241)	(0.186)	(0.185)
Observations	3,298	3,298	3,298	3,298	3,298	3,298	3,298	3,298
R-squared	0.202	0.214	0.202	0.215	0.180	0.191	0.180	0.195

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.6A. Density distribution margins for all shared membership models.

VARIABLES	10%	20%	30%	40%	50%
Margins at density = 0.2	**0.655*** **	**0.616*** **	**0.837*** **	**0.906*** **	**0.977*** **
	(0.123)	(0.108)	(0.0872)	(0.0746)	(0.0675)
Margins at density = 0.4	**1.557*** **	**1.395*** **	**1.296*** **	**1.190*** **	**1.188*** **
	(0.0604)	(0.0528)	(0.0427)	(0.0365)	(0.0331)
Margins at density = 0.6	**2.038*** **	**1.789*** **	**1.504*** **	**1.325*** **	**1.273*** **
	(0.0343)	(0.0300)	(0.0243)	(0.0208)	(0.0188)
Margins at density = 0.8	**2.098*** **	**1.801*** **	**1.460*** **	**1.311*** **	**1.230*** **
	(0.0388)	(0.0339)	(0.0274)	(0.0234)	(0.0212)
Margins at density = 1	**1.737*** **	**1.429*** **	**1.166*** **	**1.148*** **	**1.061*** **
	(0.0767)	(0.0671)	(0.0542)	(0.0464)	(0.0420)
Observations	3,298	3,298	3,298	3,298	3,298

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.6B. Centralization distribution margins for all shared membership models.

VARIABLES	10%	20%	30%	40%	50%
Margins at centralization = 0	**1.461*** **	**1.196*** **	**1.069*** **	**1.089*** **	**1.036*** **
	(0.0628)	(0.0549)	(0.0443)	(0.0379)	(0.0342)
Margins at centralization = 0	**1.997*** **	**1.715*** **	**1.430*** **	**1.297*** **	**1.241*** **
	(0.0328)	(0.0287)	(0.0231)	(0.0198)	(0.0179)
Margins at centralization = 0	**2.076*** **	**1.817*** **	**1.511*** **	**1.334*** **	**1.282*** **
	(0.0322)	(0.0281)	(0.0227)	(0.0194)	(0.0175)
Margins at centralization = 0	**1.699*** **	**1.502*** **	**1.313*** **	**1.200*** **	**1.160*** **
	(0.0397)	(0.0347)	(0.0280)	(0.0240)	(0.0217)
Margins at centralization = 0	**0.866*** **	**0.771*** **	**0.836*** **	**0.894*** **	**0.875*** **
	(0.0982)	(0.0858)	(0.0693)	(0.0593)	(0.0535)
Observations	3,298	3,298	3,298	3,298	3,298

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix A: Cox Proportional Hazards Model Results

Table A1. Cox Proportional Hazards model results, 10-30%.

VARIABLES	10%				20%				30%			
Density	0.884	**0.0111*** **			0.956	**0.0238*** **			**1.128* **	**0.109*** **		
	(0.101)	(0.00377)			(0.0861)	(0.00661)			(0.0775)	(0.0239)		
Density squared		**25.37*** **				**15.59*** **				**5.760*** **		
		(5.747)				(2.925)				(0.891)		
Centralization			**0.989**	**0.0695*** **			**0.934**	**0.0999*** **			**0.926** **	**0.208*** **
			(0.0643)	(0.0114)			(0.0484)	(0.0143)			(0.0359)	(0.0258)
Centralization squared				**45.74*** **				**24.78*** **				**8.467*** **
				(10.30)				(4.785)				(1.402)
Community size	0.964***	0.960***	0.966***	0.970***	0.969***	0.966***	0.970***	0.973***	0.978***	0.976***	0.976***	0.979***
	(0.00369)	(0.00337)	(0.00298)	(0.00275)	(0.00325)	(0.00290)	(0.00275)	(0.00248)	(0.00274)	(0.00247)	(0.00236)	(0.00213)
Community size squared	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
	(4.57e-05)	(3.19e-05)	(4.33e-05)	(3.57e-05)	(4.05e-05)	(2.53e-05)	(3.87e-05)	(2.99e-05)	(3.43e-05)	(2.28e-05)	(3.33e-05)	(2.62e-05)
Community % white	0.870***	0.862***	0.872***	0.874***	0.889***	0.879***	0.890***	0.891***	0.918***	0.912***	0.916***	0.916***
	(0.0343)	(0.0332)	(0.0343)	(0.0330)	(0.0301)	(0.0293)	(0.0300)	(0.0292)	(0.0255)	(0.0248)	(0.0254)	(0.0249)
Community % male	0.762***	0.794***	0.764***	0.792***	0.803***	0.825***	0.806***	0.822***	0.870***	0.879***	0.871***	0.875***
	(0.0462)	(0.0470)	(0.0462)	(0.0449)	(0.0403)	(0.0408)	(0.0404)	(0.0395)	(0.0342)	(0.0335)	(0.0341)	(0.0323)
Complaint type	1.003	0.993	1.008	1.001	0.995	0.990	0.999	0.995	1.024	1.019	1.023	1.019
	(0.0373)	(0.0364)	(0.0374)	(0.0361)	(0.0311)	(0.0302)	(0.0313)	(0.0298)	(0.0241)	(0.0233)	(0.0241)	(0.0229)
Unit	0.767***	0.777***	0.766***	0.779***	0.746***	0.744***	0.745***	0.748***	0.940	0.943	0.939	0.943
	(0.0777)	(0.0750)	(0.0777)	(0.0744)	(0.0772)	(0.0748)	(0.0771)	(0.0742)	(0.0559)	(0.0548)	(0.0559)	(0.0548)
Community unit diversity	0.973	0.966	0.972	0.970	0.981	0.976	0.981	0.980	0.993	0.990	0.994	0.994
	(0.0448)	(0.0371)	(0.0446)	(0.0365)	(0.0414)	(0.0351)	(0.0411)	(0.0350)	(0.0395)	(0.0352)	(0.0394)	(0.0353)
Community complaint diversity	0.945	0.999	0.950	1.013	0.961	1.008	0.968	1.023	0.937*	0.970	0.939*	0.980
	(0.0383)	(0.0377)	(0.0384)	(0.0368)	(0.0363)	(0.0355)	(0.0364)	(0.0352)	(0.0314)	(0.0310)	(0.0315)	(0.0311)
Observations	3,316	3,316	3,316	3,316	3,316	3,316	3,316	3,316	3,316	3,316	3,316	3,316

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2. Cox Proportional Hazards model results, 40 & 50%.

VARIABLES	40%				50%			
Density	1.069	**0.270*** **			**1.162*** **	**0.390*** **		
	(0.0612)	(0.0496)			(0.0590)	(0.0630)		
Density squared		**2.808*** **				**2.274*** **		
		(0.368)				(0.268)		
Centralization			**0.976**	**0.396*** **			0.960	**0.427*** **
			(0.0301)	(0.0426)			(0.0260)	(0.0422)
Centralization squared				**3.632*** **				**3.174*** **
				(0.518)				(0.413)
Community size	0.984***	0.983***	0.983***	0.985***	0.989***	0.988***	0.987***	0.988***
	(0.00227)	(0.00210)	(0.00193)	(0.00177)	(0.00212)	(0.00196)	(0.00185)	(0.00170)
Community size squared	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
	(2.60e-05)	(1.79e-05)	(2.51e-05)	(1.97e-05)	(2.51e-05)	(1.86e-05)	(2.47e-05)	(1.99e-05)
Community % white	0.951**	0.946**	0.950**	0.949**	0.959*	0.955**	0.956**	0.955**
	(0.0227)	(0.0222)	(0.0227)	(0.0222)	(0.0218)	(0.0213)	(0.0217)	(0.0212)
Community % male	0.924**	0.929**	0.923**	0.927**	0.924***	0.929**	0.923***	0.927***
	(0.0294)	(0.0291)	(0.0294)	(0.0287)	(0.0269)	(0.0267)	(0.0269)	(0.0263)
Complaint type	1.032	1.028	1.031	1.027	1.055***	1.051***	1.052***	1.048***
	(0.0210)	(0.0206)	(0.0210)	(0.0204)	(0.0170)	(0.0169)	(0.0171)	(0.0169)
Unit	0.932	0.933	0.931	0.934	0.957	0.957	0.955	0.958
	(0.0522)	(0.0515)	(0.0523)	(0.0519)	(0.0530)	(0.0523)	(0.0530)	(0.0527)
Community unit diversity	0.983	0.983	0.984	0.985	0.991	0.991	0.993	0.993
	(0.0232)	(0.0220)	(0.0232)	(0.0216)	(0.0199)	(0.0191)	(0.0201)	(0.0188)
Community complaint diversity	0.973	0.993	0.973	0.997	0.995	1.011	0.993	1.016
	(0.0257)	(0.0259)	(0.0257)	(0.0259)	(0.0235)	(0.0238)	(0.0237)	(0.0237)
Observations	3,316	3,316	3,316	3,316	3,316	3,316	3,316	3,316

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix B: Structural Holes as Community Fragmentation

Table B1. Results at shared membership thresholds 10% – 30 %.

VARIABLES	10%			20%			30%		
Density			**8.303*** **			**7.101*** **			**4.384*** **
			(0.654)			(0.573)			(0.463)
Density squared			**-5.680*** **			**-5.005*** **			**-3.276*** **
			(0.461)			(0.404)			(0.327)
Structural Holes	-0.000792	**0.124** **	-0.0279	0.0415	**0.148*** **	0.0128	0.0287	**0.0712**	-0.0187
	(0.0354)	(0.0628)	(0.0625)	(0.0310)	(0.0550)	(0.0548)	(0.0248)	(0.0441)	(0.0443)
Structural Holes squared		**-0.0157** **	**-0.0129** **		**-0.0134** **	**-0.0105***		**-0.00532**	**-0.00293**
		(0.00650)	(0.00636)		(0.00569)	(0.00557)		(0.00456)	(0.00451)
Community size	0.0693***	0.0617***	0.0905***	0.0578***	0.0514***	0.0724***	0.0465***	0.0440***	0.0525***
	(0.00558)	(0.00639)	(0.00763)	(0.00488)	(0.00559)	(0.00669)	(0.00391)	(0.00448)	(0.00541)
Community size squared	-0.000588***	-0.000487***	-0.000448***	-0.000494***	-0.000408***	-0.000351***	-0.000388***	-0.000354***	-0.000288***
	(6.14e-05)	(7.43e-05)	(7.64e-05)	(5.38e-05)	(6.50e-05)	(6.69e-05)	(4.31e-05)	(5.21e-05)	(5.41e-05)
Community percent white	0.236***	0.232**	0.269***	0.196**	0.193**	0.220***	0.153**	0.152**	0.164***
	(0.0906)	(0.0906)	(0.0885)	(0.0793)	(0.0793)	(0.0775)	(0.0636)	(0.0636)	(0.0627)
Community percent male	0.315*	0.315*	0.264	0.297*	0.297*	0.250*	0.208*	0.208*	0.176
	(0.177)	(0.177)	(0.172)	(0.155)	(0.155)	(0.151)	(0.124)	(0.124)	(0.122)
Complaint type	0.0126	0.0155	0.0296	-0.00765	-0.00524	0.00524	-0.0550	-0.0541	-0.0497
	(0.0776)	(0.0776)	(0.0757)	(0.0680)	(0.0679)	(0.0663)	(0.0544)	(0.0544)	(0.0536)
Unit	0.465**	0.459**	0.426**	0.413**	0.409**	0.378**	0.209	0.207	0.185
	(0.209)	(0.209)	(0.204)	(0.183)	(0.183)	(0.179)	(0.147)	(0.147)	(0.145)
Community unit diversity	-0.0226	-0.0194	-0.0242	-0.0302	-0.0275	-0.0303	-0.0272	-0.0261	-0.0261
	(0.124)	(0.124)	(0.121)	(0.109)	(0.109)	(0.106)	(0.0871)	(0.0871)	(0.0858)
Community complaint diversity	0.0536	0.0470	-0.0242	0.0314	0.0258	-0.0434	0.109*	0.107*	0.0533
	(0.0864)	(0.0864)	(0.0848)	(0.0756)	(0.0756)	(0.0743)	(0.0606)	(0.0606)	(0.0601)
Community death *(dummy)*	-1.541***	-1.551***	-1.348***	-1.270***	-1.279***	-1.100***	-0.947***	-0.951***	-0.835***
	(0.237)	(0.237)	(0.232)	(0.208)	(0.208)	(0.203)	(0.166)	(0.167)	(0.164)
Constant	1.930***	1.859***	-0.961**	1.828***	1.768***	-0.484	1.637***	1.613***	0.426
	(0.347)	(0.348)	(0.443)	(0.304)	(0.304)	(0.388)	(0.243)	(0.244)	(0.314)
Observations	3,298	3,298	3,298	3,298	3,298	3,298	3,298	3,298	3,298
R-squared	0.199	0.200	0.239	0.207	0.209	0.247	0.212	0.213	0.237

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B2. Results at shared membership thresholds 40% & 50%.

VARIABLES	40%			50%		
Density			**2.777*** **			**2.335*** **
			(0.396)			(0.358)
Density squared			**-2.025*** **			**-1.811*** **
			(0.280)			(0.253)
Structural Holes	-0.00320	**0.0197**	-0.0355	-0.0258	**-0.00847**	-0.0585*
	(0.0211)	(0.0374)	(0.0379)	(0.0191)	(0.0338)	(0.0343)
Structural Holes squared		**-0.00287**	**-0.00152**		**-0.00217**	**-0.000676**
		(0.00387)	(0.00385)		(0.00350)	(0.00349)
Community size	0.0344***	0.0331***	0.0397***	0.0310***	0.0299***	0.0329***
	(0.00332)	(0.00381)	(0.00463)	(0.00300)	(0.00344)	(0.00418)
Community size squared	-0.000261***	-0.000243***	-0.000209***	-0.000247***	-0.000233***	-0.000187***
	(3.66e-05)	(4.43e-05)	(4.63e-05)	(3.31e-05)	(4.00e-05)	(4.18e-05)
Community percent white	0.0897*	0.0890*	0.0979*	0.0814*	0.0808*	0.0855*
	(0.0540)	(0.0540)	(0.0536)	(0.0488)	(0.0488)	(0.0485)
Community percent male	0.116	0.116	0.0959	0.108	0.108	0.0889
	(0.105)	(0.105)	(0.104)	(0.0951)	(0.0951)	(0.0944)
Complaint type	-0.0599	-0.0593	-0.0560	-0.0969**	-0.0965**	-0.0949**
	(0.0462)	(0.0462)	(0.0459)	(0.0418)	(0.0418)	(0.0415)
Unit	0.194	0.193	0.180	0.119	0.119	0.106
	(0.125)	(0.125)	(0.124)	(0.113)	(0.113)	(0.112)
Community unit diversity	-0.00270	-0.00213	-0.00260	-0.00380	-0.00337	-0.00278
	(0.0740)	(0.0740)	(0.0734)	(0.0669)	(0.0669)	(0.0664)
Community complaint diversity	0.0473	0.0460	0.0151	0.00250	0.00158	-0.0305
	(0.0514)	(0.0515)	(0.0514)	(0.0465)	(0.0465)	(0.0465)
Community death *(dummy)*	-0.930***	-0.932***	-0.860***	-0.724***	-0.725***	-0.662***
	(0.141)	(0.141)	(0.141)	(0.128)	(0.128)	(0.127)
Constant	1.678***	1.664***	0.858***	1.572***	1.562***	1.002***
	(0.207)	(0.207)	(0.269)	(0.187)	(0.187)	(0.243)
Observations	3,298	3,298	3,298	3,298	3,298	3,298
R-squared	0.202	0.202	0.216	0.181	0.181	0.194

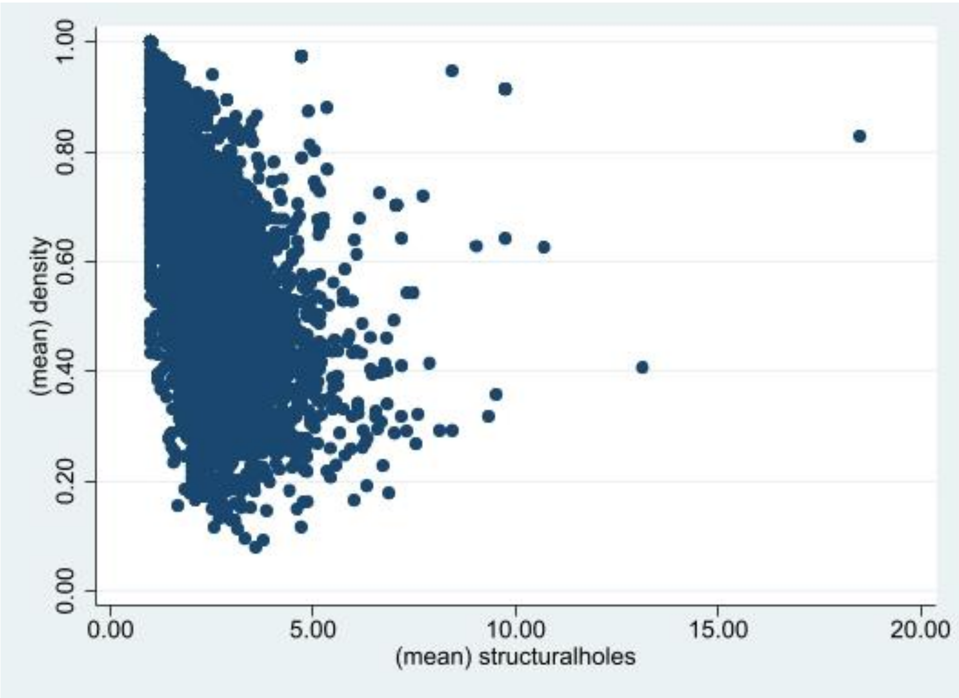
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B3. Structural holes distribution margins for all shared membership models.

VARIABLES	10%	20%	30%	40%	50%
Margins at structural holes = 1	**1.735*** **	**1.451*** **	**1.277*** **	**1.220*** **	**1.202*** **
	(0.0548)	(0.0480)	(0.0385)	(0.0327)	(0.0296)
Margins at structural holes = 4	**1.873*** **	**1.695*** **	**1.410*** **	**1.236*** **	**1.144*** **
	(0.0731)	(0.0640)	(0.0513)	(0.0436)	(0.0394)
Margins at structural holes = 7	**1.728*** **	**1.698*** **	**1.448*** **	**1.201*** **	**1.047*** **
	(0.172)	(0.151)	(0.121)	(0.103)	(0.0929)
Margins at structural holes = 10	**1.301*** **	**1.461*** **	**1.391*** **	**1.114*** **	**0.911*** **
	(0.343)	(0.300)	(0.240)	(0.204)	(0.185)
Margins at structural holes = 13	**0.592**	**0.983***	**1.237*** **	**0.975*** **	**0.736** **
	(0.626)	(0.548)	(0.439)	(0.373)	(0.337)
Observations	3,298	3,298	3,298	3,298	3,298

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure B1. Relationship between community density and structural holes.
X axis: community structural holes; Y axis, community density



Chapter IV: Those Who Hate Together Stay Together? Community Persistence in a White Supremacist Online Chat Forum

INTRODUCTION

Technological developments in the past two decades have facilitated new mechanisms for connection among people: namely, the advent of the online group (Plant, 2004). While online groups as organizational forms in many ways mirror the functionality of traditional groups that are "offline" – allowing individuals to connect with others based on similar interests for information and support, and to share ideas (Rainie & Wellman, 2012) – there also exists a darker side to such groups online: particularly, the amplification and proliferation of extremist content, beliefs, and calls to action (Medierad, 2013).

Online extremism is a serious and growing problem that poses significant threats to society and social institutions (Holt, Freilich, & Chermak, 2020; Muthukrishna, Francois, Pourahmadi, & Henrich, 2017). Specifically, extremist online groups – comprised of people who come together to discuss hate-based ideologies, concerns, and ambitions – have been shown to generate serious harm and consequences for broader society (Iqbal & Townsend, 2019). Indeed, many high-profile attacks, such as mass shootings in El-Paso, Texas, and Oslo, Norway, in recent years have been carried out by individuals affiliated with online extremist organizations (Comerford, 2020; Verini, 2023). A growing body of evidence suggests that such online groups are key facilitators of violent extremism (Gaudette, Scrivens, & Venkatesh, 2022) in that ongoing exposure to violent, extremist ideologies helps cultivate a radicalization towards violence (Bouchard & Nash, 2015; Potok, 2015). Given the high-stakes nature of the behavior that these groups can foment, research has called for more exploration of these organizational forms on the so-called "fringes" of society, as doing so may shed light on extreme versions of organizational misconduct (Palmer et al., 2016a; Greve, Palmer, et al., 2010). In particular, researchers have called for a better understanding of how these groups are structured, as well as the role of network relationships in magnifying and proliferating their agendas (Halavais, 2015; Greve, Rao, Vicinanza, & Zhou, 2022; Bouchard & Levey, 2015)

Recent work has highlighted that online extremist groups tend to be fragmented in nature (Comerford, 2020; Berger, 2019) and that, as a result, they are often comprised of many smaller sub-groups, or communities (Baele, Brace, & Coan, 2021). In this study, I employ a network community level of analysis to examine how social cohesion and structural inequality influence the persistence of such communities over time. I leverage data from a white supremacist online chat forum to test these relationships. The question of longevity is an important one, as the risk of violence and harm increases the longer individuals are exposed to extremist language and content on these forums (Iqbal & Townsend, 2019; Verini, 2023). I use the Louvain community detection algorithm (Jain et al., 2022) and locate 1,002 unique communities over 11 years of data (2002 – 2012) comprised of 15,956 white supremacists linked by 74,476 threads they share in common.

THEORETICAL BACKGROUND

Online groups as organizational forms

Organizational research first began to explore the social structure of an online group in the early 2000s, as the proliferation of low-cost access to the internet first helped normalize the online interactions of dispersed groups of people with shared interests (Norris, 2002; Plant, 2004). These internet-based groups became generally referred to as “online groups” and they exhibit a wide range of characteristics and purposes (Wilson & Peterson, 2002). Much like more traditional group forms, online groups provide spaces (albeit virtual) where individuals can connect with each other over shared values and ideas (Rainie & Wellman, 2012). Online groups connect people on a wide range of interests and purposes, including professional networking (Baumann & Utz, 2021), political activism (McCaughey & Ayers, 2003), and social endeavors such as hobbies and fandom related to movies or bands (Chen & C.S. Ku, 2013; Norman, 2014).

Just as some groups exist “offline” with the intent of sharing and spreading violent and extreme viewpoints, the internet has similarly engendered online extremist groups. Online radicalization is a rapidly-growing phenomenon (Speckhard, Warren, Strezishar, & April, 2022). The internet has enabled intimate connections to develop among people worldwide, regardless of location, and while that applies to more innocuous interests, it also applies to extremism. Research has begun to explore the role of this digital milieu in bolstering extremist groups online (Dalgaard-Nielsen, 2010). As a growing body of work suggests, structural and social aspects of online extremism allow such groups to flourish, promoting radicalization and harmful behaviors in the real world (Bouchard & Nash, 2015; Colleoni, Rozza, & Arvidsson, 2014).

Online extremism and the role of the group

Extremist groups have long existed in the United States and elsewhere (Mudde, 2017). Such groups are generally characterized as being united by ideologies “outside the mainstream which are damaging to individuals and societies alike” (Vu, Wilson, Chua, Shumailov, & Anderson, 2021: 1). Their behaviors are often masked by anonymity (Cunningham et al., 2016) and often encapsulate violence, discrimination, and other activities deemed illegal or otherwise harmful to others (Milward, 2015; Raab, 2003). Such groups subscribe to a “worldview where hate is a driving force and violence a legitimate resource” (Medierad, 2013: 2).

Extremist groups began developing online presences in the early days of the internet (Gerstenfeld, Grant, & Chiang, 2003). Indeed, the proliferation of the internet enabled extremist groups to spread their messages and recruit new members who would have once been unreachable (Agarwal & Sureka, 2015; Speckhard et al., 2022). Access to such digital spaces engendered a shift whereby online connections to extremist culture and ideologies became as important, or even more so, as connections to such groups “on the ground” (Comerford, 2020). Digital platforms provided a permissive space where extreme and violent activities and beliefs can be shared and explicitly endorsed (Berger, 2019; Hoffman & Clarke, 2020). As a result, online extremist groups became breeding grounds for radicalization through social ties and social influence (Hegghammer, 2006; Bouchard & Levey, 2015) and cultivated virtual echo chambers of hate-based ideologies and content (Ducol, 2015; Davey & Ebner, 2019; Colleoni et al., 2014).

Thus, online extremist groups provide supportive social containers wherein individuals can engage with both content and other members in an ongoing social process (Dalgaard-Nielsen, 2010; Steiner & Onnerfors, 2018). Indeed, research on so-called “lone wolf” perpetrators of violence and terrorist attacks have noted that these agents are often (in)directly supported by their socialization within extremist groups online (Feldman, 2018; Macklin, 2019). Such behaviors can thus be understood within the context of participation in online extremist groups as a broader social process rather than isolated incidents (Granovetter, 1978). And yet, we know very little about the social and organizational aspects of these online groups (Bouchard & Levey, 2015; Steiner & Onnerfors, 2018). Researchers have called for more integration of network concepts and methods to better understand the structural features of these groups

(Cunningham et al., 2016; Greve et al., 2022; Cunningham & Everton, 2022). In this study I help address these calls and focus on a particular feature of network research: that of the network community.

Structural characteristics and conflicting goals of online extremist groups

Existing work suggests that online extremist groups are increasingly decentralized in nature and are often fragmented into smaller sub-groups within the broader network (Baele et al., 2021; Verini, 2023). Many types of "illicit" organizational settings – such as the Mafia, drug cartels, or terrorist groups (Calderoni, 2012; Shapiro, 2013) – have fragmented organizational structures that are well-suited to a network community level of analysis. Indeed, in the case of online extremist groups, this fragmentation is common and reflects splintering into increasingly extreme communities (McCauley & Moskalenko, 2008). To understand how such communities survive over time, I incorporate an institutional perspective and suggest that these communities exert their own normative pressures and monitoring capabilities to enforce conformity among members.

From a social cohesion perspective, research indicates that structural density acts as an effective governance mechanism (Aven et al., 2019; Axelrod, 1984; Podolny, 1993) and that, as a result, as a group's level of social cohesion increases, its ability to establish cooperative norms as well as collective monitoring also increases (Coleman, 1988; Baum et al., 2007; Rowley, 1997; Greve, Baum, et al., 2010). Indeed: one key component of online extremist groups is the ability to monitor and sanction particular behaviors or beliefs while teaching and encouraging others, such as by commenting encouragingly (or derogatively) on particular posts, or retweeting particular messages to boost support for specific content more broadly (Agarwal, 2014; Agarwal

& Sureka, 2015). Strong cohesion is the primary way that online extremist groups foster a separate ecosystem of alternative beliefs and ideologies, within which members can feel they truly belong (Colleoni et al., 2014). However, social cohesion can also be negative for groups in that it jeopardizes their ability to maintain some degree of protection from outsiders. In the context of online extremist groups, disruption from law enforcement is an ever-present threat. Due to the nature of their organizing – on online platforms – infiltration by federal authorities is always possible and risks arrests or inconvenient exposure (Makuch, 2020). Members often try to ferret out others who they think may be acting suspiciously and can eject those who they suspect may be imposters (Bowman-Grieve, 2009).

From a structural inequality perspective, the power of community norms and monitoring capabilities depends on the relatively equal distribution of ties in the community: effective norm distribution is most likely to occur when multiple members experience similar levels of normative constraints (Burt, 1992b; Coleman, 1990). In the context of online extremist groups, structural equality is somewhat baked into the overall organizational form (Davey & Ebner, 2019). Such groups often strive for some degree of a "leaderless resistance" in which it becomes more difficult for hostile outsiders to identify and target important members (Byman, 2017). Thus, a more decentralized group structure both can act as a protective mechanism from would-be interlopers with equal risk and equal monitoring shared among all members (Everton & Cunningham, 2015). At the same time, structural inequality does have many benefits. It promotes coordination among members and can help communities be more efficient (Morselli, 2009; Morselli et al., 2007) and mobilize key resources (Enders & Jindapon, 2010). This kind of functionality is important for entities such as online extremist groups, who balance security needs with a desire to follow key leaders (Potok, 2015). Despite longstanding calls to maintain leaderless structures, research shows that extremist groups do identify and cluster around figureheads who educate new members and communicate important rules and expectations. For example, members viewed as having more knowledge or status are more likely to have their content shared by others (Cunningham & Everton, 2022; Speckhard et al., 2022). Such figureheads are also more likely to moderate the behavior or comments of others (Kleinberg, van der Vegt, & Gill, 2021). Thus, though these groups are somewhat fragmented by nature, members still look for others in charge to tell them what they can (or can't) and should (or shouldn't) do to keep their communities healthy and in line (Colleoni et al., 2014; Gaudette et al., 2022).

EMPIRICAL SETTING AND DATA

I test my hypotheses using data scraped from Whitestorm[7], a large and long-running white supremacy chat forum in the world. Research has characterized these types of groups as those that violate laws, social rules, or norms, and are united by goals and ideologies based on wrongdoing in some form (Cunningham & Everton, 2022; Cunningham et al., 2016; Everton, 2012), and scholars have called for more exploration of this type of misconduct on the so-called fringes of society (Greve et al., 2010; Palmer et al., 2016). I focus on an extremist white supremacy chat forum, as such groups are widely recognized as posing a significant threat to safety in the United States (Freilich, Chermak, Belli, Gruenewald, & Parkin, 2014) and to democratic social institutions more broadly (Fox, 2022; Muthukrishna et al., 2017). Whitestorm, due to its size, duration, and position in the white supremacist ecosystem, provides a compelling

[7] Name changed to protect privacy, and in adherence to compliance requirements per data provider.

and unique strategic case (Merton, 1968: 162–165) to explore the broader context within which it exists.

Exposure to these spaces – and the supremacist, extremist content wherein – has been linked to significant offline violence (Iqbal & Townsend, 2019). Indeed, F.B.I. counterterrorism officials reported to Congress in 2019 that "individuals adhering to racially motivated violent extremism ideology have been responsible for the most lethal incidents among domestic terrorists in recent years" (Verini, 2023). In 2019, high-profile attacks in New Zealand, the US, Germany, and Norway were committed by individuals connected to extreme-right networks largely operating online (Comerford, 2020). Such affiliation has been linked to, among others, mass shootings in El Paso (Macklin, 2019), hate crimes against immigrants (Müller and Schwarz 2020), and antisemitic violence (Finkelstein et al., 2023) as well as violence between ethnic communities (Sudhakar et al., 2022). A recent New America Foundation report found that nearly 100 people were killed by white supremacist terrorists between 2001 – 2016 in the United States (Plucinska, 2015). From 1990 – 2010, 145 acts of violence committed by the American far-right resulted in 348 deaths (Werleman, 2014). A growing body of evidence thus suggests that the internet is a key facilitator of violent extremism (Gaudette et al., 2022) in that ongoing exposure to violent, extremist ideologies, as well as inflammatory language and content, helps cultivate a radicalization towards violence (Potok, 2015).

Setting background

"Our prime directive – We must secure the existence of our people and a future for White children. We want an area on Earth reserved for Whites, and Whites only, where we can live in peace apart from the horrors of other races who would do us harm. Our children deserve to live

in a First World European civilization among their own kind, as our ancestors did, and we owe that to them. This is the basic principle of ‘White Nationalism’ (WN). This is what we want.”[8]
– From *Introduction to Whitestorm and the Pro-White Movement: What we want, and why.*

“Why would anyone in their right mind allow immigration from places like Iraq, Somalia and Mexico into the United States and Europe? This brings us to the terrible truth of the ‘Jewish problem’. It was the Jews. The Jews have been working together behind the scenes to gain control of all the TV stations, schools, newspapers, radio stations, governments, movie studios, banks, etc. to destroy all potential rival groups and rule the world. The origin of the problem with the Jews is, once again, in their blood. As a group, a distinctive race, they suffer from psychopathy - a mental disorder whose main symptom is the ability to lie without any empathy for people unlike themselves. That is the little secret to their success.”
– From *Introduction to Whitestorm and the Pro-White Movement: What we want, and why.*

Whitestorm was founded by a former Ku Klux Klan boss in the mid-1990s and was among the first major hate sites on the internet. The site focuses on propagating white nationalism, Nazism, antisemitism and islamophobia, as well as anti-feminism, homophobia, Holocaust denial, and white supremacy. It is among the most popular forum for white supremacists to share articles, engage in discussions, and post news of upcoming racist events. Whitestorm’s structure focuses on community building in that it is organized as a message board. Members can post opinions and read others’ responses, thus cultivating a sense of dialogue and, ultimately, a genuine white supremacist cyber-community (Southern Poverty Law Center, 2023).

Whitestorm is a publicly-available group: anyone can access its website online. However, many threads are not available to be viewed unless one has a user account registered with the group, and only registered members are allowed to post. The site is organized into several boards, within which multiple threads exist. Members post comments on threads. As of December 2020, Whitestorm had 147 boards and 727,518 unique threads associated with them, within which 129,536 members posted 9,761,344 posts. Boards, threads, and posts cover a wide

[8] Exact quotes modified for confidentiality purposes, in adherence to compliance requirements per data provider.

range of topics. Board names include Politics and Activism; Covid-19; Newslinks and Articles; Trades and Skills; Nature and Environment; Youth; Gaming; and 9/11 Truth. Within these, threads include a wide range of topics such as “Blacks: The Cost Is Too Great”; “Race: They Are Faking It”; “What Happened to America?”; and “Very Interesting Jewish vs white IQ diagrams.” In addition to these topics, there are other familiar markers of an engaged community: there are frequent birthday greetings, essay contests, and tips shared for getting a newborn to sleep or recipe recommendations. Yet interspersed among all of these topics are ultimately the main values and concerns of the group: that of racial superiority, fear of interracial mixing, and the secret conspiracy of Jewish people to subjugate white people.

Members are heavily invested in establishing a clear normative environment and do so through encouraging certain content and discouraging other types. For example, one member posted asking whether they could be accepted into Whitestorm even though they were gay: they said that they felt most at home with the white supremacist community but wanted to clarify Whitestorm’s policy on homosexuality. A moderator replied:

> “Homosexuality is not welcome on Whitestorm, and no arguments in favor of homosexuality will change that. We've heard it all, and our Administrators have made the official Whitestorm stance on this issue clear. All threads advocating Homosexuals will be deleted, and any attempts to further any homosexual agenda on Whitestorm will not be tolerated.”

Similarly, throughout the chat forum there is suspicion regarding interlopers, and tips on how to weed out potential outsiders posing as white supremacists. In particular, members fear infiltration by Jewish people, and advise:

> “Here is something else to know about the Jews - they try to infiltrate groups opposed to them. Seriously. Once they get inside a group, they try to rot it from the inside out either by radicalizing it until good people are appalled by it, by moderating it until it becomes meaningless, or by sowing the seeds of internal confusion, disagreement and chaos. Keeping Jews out of pro-White groups is a full-time job. However, it can be fun trying to ‘spot the Jew’. (Hint: They don't generally like to acknowledge or talk about the Jewish problem and they often

like to spread ‘hate’ and cause arguments in order to cause division and drive away decent folks.)”

A clear relationship exists between the behaviors of members online and subsequent offline behaviors and consequences. In April of 2014, the Southern Poverty Law Center published results from a two-year Intelligence Report entitled “White Homicide Worldwide” documenting nearly 100 murders committed by members of Whitestorm between 2009 and 2014. The site has suffered several interruptions from external stakeholders in an attempt to mitigate its influence online and / or punish users directly: in 2002, Google removed Whitestorms’ website from its French and German indexes in compliance with legislation in those countries forbidding links to websites such as Whitestorm. In 2012, Italian police blocked the website and arrested four members for inciting racial hatred, after a blacklist of “prominent Jews and people who support Jews and immigrants” was published on the Italian section of the website. The subsequent year, in November 2013, Italian police raided the homes of 35 Whitestorm members, one of whom had two loaded weapons, a hand grenade casing, and a flag with a swastika in his possession. And in August 2017, Whitestorm’s domain name was seized by its registrar for “displaying bigotry, discrimination or hatred.” The site came back online a month later.

Key terms and level of analysis

Misconduct network communities

I leverage a broad definition of misconduct as pertaining to a wide range of behaviors that violate a standard of appropriateness, ethicality, legality, or normative legitimacy (Greve, Palmer, et al., 2010; Palmer et al., 2016a). In this study I operationalize misconduct as posting on Whitestorm. There are a number of ways one could plausibly measure misconduct in this setting.

For example, some existing work leverages topic modeling to trace how specific types of extremist language evolve over time. Abbasi and Chen (2007) hand-crafted specific lexicons for hate and violence to measure affect intensities on American and Middle Eastern extremist forums to compare language use among both groups. Kleinberg and colleagues (2021) similarly modelled extremist language to test different temporal trajectories of such language over time.

These types of research questions are important and seek to understand the prevalence and intensity of extremist language. And indeed, my dataset allows me to track sentiment and toxicity of specific content within Whitestorm using categorization from Google's Perspective API, which evaluates each post across a range of emotional concepts using machine learning models. However, while splicing out specific content would be a worthwhile avenue for future work, I believe it is important to first understand behavior on this forum *overall*, as ultimately members have self-selected into this group due to an interest in its values and goals, through which they can find like-minded people and build relationships. As such, even if they are not explicitly discussing white supremacist content in a particular post (such as recipe sharing), members are still ultimately interacting within a normative environment that promotes white supremacy, violence, and hate-based ideals (Gaudette et al., 2022). And indeed, extant research has indicated that simple exposure to these groups and the wide-ranging topics within them can ultimately normalize and risk extreme and violent behavior offline (Potok, 2015). Because of this, I focus on *all* posts within Whitestorm, and encourage future work to examine more specific topics to assess how language use may evolve over time[9].

[9] For robustness purposes I do conduct this analysis on a subset of severely toxic threads. I take the average of thread severity and run the analysis on threads averaging greater than 0.5 severe toxicity. Results are generally robust to this sample. Please refer to **Appendix C** for more details and results.

With this in mind, this study explores the longevity of network communities as identified within Whitestorm. Recent work has suggested that extremist online forums are often fragmented into smaller sub-pockets represented by network communities (Baele et al., 2021). This fragmentation reflects splintering, or "fission," into increasingly extreme niches (McCauley & Moskalenko, 2008). In an effort to capture this fragmentation quantitatively, I construct misconduct network communities by capturing ties between members based on threads they have posted on in common.

Data and sample

I worked closely with the Cybercrime Center at the University of Cambridge to obtain these highly sensitive data. Over a period of six months in 2020, I worked with their team and the University of Michigan to ensure all compliance measures and legal procedures were met to ensure the safety of myself and of the researchers at the Center. This includes a unique login and password to access the data that only I can access through a two-layered facial recognition software followed by a unique password that only I know, of which no written record exists. The Cybercrime Center mines and correlates these datasets for the purpose of helping academics study these issues, as well as to support law enforcement when possible and applicable. Accessing this type of information is incredibly difficult, and I am grateful to the team at the Center for facilitating its use.

My dataset is a collection of structured textual data scraped from Whitestorm and stored in PostgreSQL – an open-source relational database – dumped into text files using the SQL format. These snapshots are standalone, which means that they have the required instructions to create the database and the tables, copy the data, and create indices and primary keys. The data follow an Entity-Relationship (ER) schema: each forum has a single site which contains one or more boards. A board is a bulletin board or sub-forum within the main forum site. Each board comprises one or more threads (topics of information initiated by a member) and each thread is composed by one or more posts (one written initially and the different replies). My data is a product of the Cybercrime Center's crawling algorithms and is in text content format. From PostgreSQL I analyzed my data using STATASE 17 as well as ORA Pro 3.09.142, a network analysis and visualization software.

My data comes from a subset of over 9.7 million chat forum posts from 2002 – 2020, posted by 130,087 members across 727,518 threads. Exploring such a large, longitudinal dataset allows me to examine the longevity of relationships between among members as they develop a sense of community (Bowman-Grieve, 2009; Gerstenfeld et al., 2003) and become more entrenched within the normative frameworks of Whitestorm. **Table 1** shows summary statistics for the global population of all forum posts, within which my final analyses are run on a sample. On average, threads are comprised of 66 members and 757 posts. The average thread lasts about 1.4 years. Members are very active on the forum: the average member posted 7,025 times over nearly seven years. Taken together, this data suggests a highly dynamic, involved membership that posts many times (88.75 posts per thread) on a wide range of topics (3,114 threads) over the course of their time on the forum (nearly three times per day). Notably, this membership also has an incredibly wide range of participation, as reflected in the significant standard deviations across the global population's summary statistics.

Analytical strategy

Sampling procedure

I located network communities of Whitestorm members based on posts affiliated with the same thread. Thus, I transposed my data from a two-mode network (members by threads) to a one-mode matrix of member X member shared threads: my nodes are members and the links between them are the threads they have posted on together. To analyze the longevity of communities within Whitestorm, I needed to establish the appropriate timeframe over which to assess community duration. Based on my analysis of the full sample of all forum posts, I determined that panel data at the yearly level would be appropriate, as the average thread lasts slightly less than 1.5 years.

Given the large and highly dynamic nature of the global population, I made a few empirical decisions to best capture underlying real communities of members. The first is that I kept only threads that had at least two members posting on them (to reflect an actual interaction, rather than just one person talking to themselves) and I removed any members that only posted one time during the entire sample, as I expected that to be more likely to be random noise rather than meaningful behavior (Jain et al., 2022). Next, the wide range of thread sizes caused me to determine a conservative threshold that could conceivably reflect actual relationships occurring on a thread. I constructed the ratio of a member's posting per overall posts in a thread in an attempt to capture meaningful social interactions among members on a post. For example, in larger threads (one thread was comprised of over 10,000 posts), it would be possible for a member to post more than once, but for their overall participation in such a thread to be negligible given the large number of posts. I thus removed any members whose posting ratios were below 1% of the overall posts in a thread (a conservative measure) in an effort to weed out behaviors that are more likely to be extraneous noise than meaningful social exchanges[10]. These decisions resulted in an approximately 50% reduction in total sample size. **Table 2** indicates this next splice of my sampling procedure.

Network analysis

Having established the sample, I next ran my network analysis (2002 – 2020) to establish that the minimum empirical requirements for a statistically significant presence of a community structure were met – namely, that a minimum Newman modularity score of 0.3 was met or exceeded in all the years of my sample (Newman, 2006, 2016). I ran a community detection algorithm using the Louvain method, which has been demonstrated to accurately capture misconduct-based network communities (Jain et al., 2022; Staudt & Meyerhenke, 2016). My results indicated that in fact, the requisite Newman modularity score was only met consecutively from 2002 – 2012; thus, the community structure reflected meaningful social pockets rather than random noise only in those years. I thus removed all other years from my sample and focused only on years 2002 – 2012, given the modularity requirements. I located 394 unique communities of 22,091 members connected by 114,627 threads. **Figure 1** illustrates what the community structure looked like in 2008, in which 803 members were organized into 24 communities. Note that due to high density of links among members, this illustration reflects communities proportional to size for ease of viewing.

However, this was not my final sample. First, I am interested in misconduct as a *group* phenomenon and this sample included both isolates and dyads. I thus kept only groups that were sized three and greater and re-ran my community detection algorithm to capture the presence of *extradyadic* social structures from 2002 – 2012. Next, my data include some branching and

[10] Note that results were unchanged whether I used this measure or not, likely as it affected less than 0.05% of the sample.

reunification, in which communities can split into multiple communities and merge back into larger ones, I follow Vedres and Stark's (2010) methodology and treat each branching as its own separate community. Thus, I identify 1,002 unique communities with unique pathways over the course of my sample. **Table 3** shows the summary statistics for my final sample; **Table 4** indicates the annual distribution of communities, threads, and members in this final sample. I located 1,002 unique communities in the data of 15,956 members connected via 74,476 threads. On average, I located 91 communities per year; the average community included 316 members. The average thread in the global sample lasts approximately one year, and these threads have new posts almost every day. As threads are the basis for the community detection, establishing their longevity at the annual level seemed appropriate; however, as online behavior can exhibit shorter lifecycles (i.e., monthly; see McCaughey & Ayers, 2003) future work could explore longevity at more granular timeframes. **Figure 2** illustrates the community structure of my final sample in 2012, in which 1,013 members are linked by 5,609 threads and organized into 14 communities. Again, note that due to the high density of links among members, this illustration reflects the communities proportional to size for ease of viewing.

Dependent variable: Community longevity

To define and measure community longevity, I build on Simmel's (1898) conceptualization that a social group's persistence reflects some membership continuity in contiguous stages. An established measure of community longevity is absent from the wrongdoing literature, and importing such a measure within the context of misconduct communities is problematic. Indeed, in the context of online extremist groups, many users "lurk" and may be ingesting content without posting themselves; in this case, these relationships would be missing from my data (Nielsen, 2009; Sudhakar et al., 2022). Additionally, online forums –

both extremist and otherwise – often experience both periods of inactivity and intermittent flurries of activity (Kleinberg et al., 2021). As a result, establishing some kind of longevity measure may miss real relationships that are simply more sporadic in nature.

Despite these challenges, establishing an empirical measure for longevity remains crucial, as research demonstrates that the risk of harm and violent behaviors increases as exposure to these forums increases (Finkelstein et al., 2023; Kleinberg et al., 2021; Müller & Schwarz, 2020; Sudhakar et al., 2022). Thus, I retain the general spirit of recent work and measure group longevity via several different measures as a starting point for understanding longevity in context of misconduct. I do so by capturing shared membership thresholds in ten percent increments from 10% – 50% to establish whether a group that existed in time *t* still existed in time *t+1*.

I leverage Vedres and Stark's (2010) approach, which establishes the number of shared members between a group in time *t* ($G_{i,t}$) and in time *t+1* ($G_{j,t+1}$) as a proportion of the members from $G_{i,t}$. This method captures the extent to which the shared membership between communities is a reflection of the group at time *t* continuing into time *t+1*. For example, if a community had 20 members in time *t*, and ten of those members were also present in a community together in time *t+1*, that would be considered 50% membership continuity and the community would be considered as having "continued." Below I demonstrate this model formally.

$$MembershipOverlap_i = \frac{G_{i,t} \cap G_{j,t+1}}{G_{i,t1}} \qquad \textit{(Dependent Variable)}$$

Using these metrics, I consider $C_{i,t}$ and $C_{j,t+1}$ as a single dynamic group if the percent of shared members was greater than 10%, 20% 30%, 40%, and 50%. If the criteria as indicated in these definitions were met in a given year, I assigned the community a 1 for continuity, and assigned a 0 if otherwise. Across these definitions and shared membership thresholds, community longevity ranges from 1 to 10 years, with the average number of years ranging from one to three years depending on the threshold. Analyzing each of these separate measures of community duration allows me to include robustness with my findings, given the lack of theoretical grounding for membership thresholds within the context of misconduct network communities.

Independent variables

Social Cohesion: Density. To test the effect of overall social cohesion on community longevity, I constructed measures for density. Density measures the actual number of ties among members within-community (T_i) relative to the total number of possible ties among members (*n(n-1)/2*):

$$Density_i = \frac{T_i}{n(n-1)/2}$$

Each community has a value for density in each of the years that it existed. As my data is cross-sectional, I took the mean of density across all years that the community existed to run my regression analyses. In line with Hypothesis 1, I specified both linear and squared effects for this predictor (Haans et al., 2016; Sytch & Tatarynowicz, 2014). I also constructed a measure for density at the time of community founding and determined that my results were robust whether I used the mean value or founding value of density, as community density remained relatively stable over the course of a community's lifetime.

Structural Inequality: Centralization. To test the role of structural inequality on community longevity, I calculate measures of degree point centrality and graph degree centralization following Freeman (1978, 2014). Degree centralization measures the extent to which the ties of a given network are concentrated on a single actor or group of actors, or are instead more diffuse and equally distributed among actors. This measure of centralization is based on normalized variance in node centrality, which allows me to measure the relative importance of any given node in a community and then index the tendency of a community to gravitate towards a single (or few) node(s) than all others in the community. To do this, I first calculated the total number of ties per member per community to get a measure of member degree centrality ($C_x(p_i)$) and calculated the largest value of officer member centrality per community ($C_x(p^*)$). Next, I summed the difference between the maximum degree centrality and each node's centrality and divided it by the maximum possible sum of differences in centrality. While negatively correlative with community density, centralization sheds light not on the overall cohesion of the community but specifically the *distribution* of those relationships, capturing the extent to which this distribution is equal or unequal. Formally:

$$Centralization_i = \frac{\Sigma(C_x(p^*) - C_x(p_i))}{\max \Sigma(C_x(p^*) - C_x(p_i))}$$

Each community has a value for centralization in each of the years that it existed. As my data is cross-sectional, I took the mean of centralization across all years that the community existed to run my regression analyses. In line with Hypothesis 2, I specified both linear and squared effects for this predictor (Haans et al., 2016; Sytch & Tatarynowicz, 2014). I also constructed a measure for centralization at the time of community founding and determined that my results were robust whether I used the mean value or founding value of centralization, as community centralization remained relatively stable over the course of a community's lifetime.

Control variables

I ran my analyses controlling separately for both community size and logged community size, as these measures correlate with both density and centralization. I used a logged measure given the wide variance of community sizes, but my results were robust to using either measure of community size (logged or not). Also, as I included squared terms for my independent variables, I also included a squared term for community size; my results were robust whether I included a squared term or not.

Next, extremist online membership has been shown to wax and wane depending on real-world events (in Whitestorm, membership spiked following the election of Barack Obama in 2008 and the economic downturn shortly thereafter; (Potok, 2015)). Thus, I included founding-year fixed effects to control for any heterogeneity that might exist due to the year at which the community started. Finally, exploring longevity as a dependent variable can raise questions regarding censoring of the data. When studying duration, data censoring can arise if the community either continues after the sample concludes ("right-censoring") or if the community existed before the sample began ("left-censoring") (Lagakos, 1979). Right-censorship is more common (Leung et al., 1997) and presents a possibility of selection bias that can bias inference regarding the survival time distribution (Andersen, 2014). To assess the extent to which right-censorship may be an issue in my data, I first confirm that over 98% of communities in my sample expired before the end of the sample itself. Thus, I do not expect right-censoring to skew my results. Nonetheless, I included a dummy variable as to whether the community died during the sample's timeframe, as not all communities had died by the end of 2012 and community death correlates negatively with community longevity.

Regarding possible left-censorship, I confirm that 15.87% of communities started in 2002, the beginning of my sample. Importantly, I did not find a statistically significant network community structure before 2002, per Newman and colleagues (Newman, 2006, 2011, 2016); thus, empirically there is no statistical presence of communities to analyze prior to 2002. Similar to prior work on longevity (see Baker et al., 1998; Bertrand and Lumineau, 2016), I therefore do not expect selection bias related to left-censorship in my models, though the inclusion of time-varying fixed effects helps control for any time-based selection bias, as indicated previously. **Table 5A** notes summary statistics for my dependent, independent, and control variables; **Table 5B** notes correlation matrices for these measures. **Figure 3** depicts a graph of the relationship between my measures of social cohesion and structural inequality, as they correlate highly negatively.

Finally, I execute an ordinary least squares regression using fixed effects and robust standard errors in STATA S/E 17.0[11]. As my independent variables are highly negatively correlative, I run my models to assess each relationship independent of each other, rather than a model that includes them both together. As they are both co-determined and thus multicollinear, including them together in the same model would likely produce incorrect results (Schroeder et al., 1990; Farrar & Glauber, 1964)[12].

RESULTS

Tables 6A – 6C reveal results for all models at the 10 – 50% membership thresholds controlling for community death and community size (actual), with yearly fixed effects. Results

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[11] With cross-sectional data and a count variable as a dependent variable, either a traditional OLS regression or a Poisson regression would be appropriate (Coleman, 1964). Poisson regression models the number of occurrences of an event and calculates an incidence rate ratio to calculate the relative incidence rate of the dependent variable as the independent variable(s) change (Chatterjee & Hadi, 2006). I follow work from Gaure (2011) and Guimarães and Portugal (2010) and execute my models using OLS, as interpreting curvilinear effects with Poisson can be challenging (Coxe et al., 2009); however, I also run the analyses using Poisson and the results are robust to either method. Additionally, a Cox proportional hazards model could be appropriate as it models the relationship between covariates and risk of failure (Kleinbaum & Klein, 2012), which is a slightly different way of conceptualizing my research question. Cox models can be used for count data, but these models often do not perform as well as other models (such as OLS or Poisson) and can make interpretation difficult when modeling data with non-normal distributions (Lin & Wei, 1989), as is the case with my dataset. Nevertheless, I also run a Cox model and find the results are robust to any of the three modeling approaches, including survival analysis. Please refer to **Appendix C** for results.

[12] In an effort to mitigate multicollinearity, I also ran my analyses using number of structural holes as a measure of community fragmentation. Number of structural holes has been demonstrated to capture structural inequality within a community and can reflect fragmentation, which leads to an uneven exertion of normative constraints (Rowley et al., 2005; Burt, 1992b; Borgatti et al., 1999). Results were robust to either measure of structural inequality; please refer to **Appendix D** for results.

are robust when using logged community size instead of community size (actual). The results from my models indicate support for Hypothesis 1 at membership thresholds 20 – 50% but not at the 10% specification. Following guidance from Haans and colleagues (2016), I adhere to the following steps to confirm that my hypothesized curvilinear effects do, indeed, hold true. The first is that the first-order linear term for the independent variable must be included in the regression (Aiken et al., 1991). A significant and negative squared term indicates the inverted U-shaped relationship that I hypothesized in H1: community density is first associated with increased community longevity, but eventually it reaches a tipping point and becomes associated with *decreased* community longevity. However, though necessary, a significant squared term alone is not sufficient to establish a quadratic relationship (Lind & Mehlum, 2010). The slope needs to be sufficiently steep at both ends of the data range. In **Table 7A** I calculate the margins at several points along the density distribution to show that the slope is significant at the 95% confidence interval. **Figures 3 – 6** depict graphically these margins plots and show that the turning point is located well within my data range. Taken together, these results suggest that overall, community density does exert a curvilinear effect on community longevity and thus Hypothesis 1 is supported at the 20 – 50% membership threshold models.

Next, the results from my models also indicate support for Hypothesis 2 at membership thresholds 20 – 50% but not at the 10% specification. I replicate my steps from H1 based on Haans and colleagues (2016) to confirm that my hypothesized curvilinear effects do, indeed, hold true. The first is that the first-order linear term for the independent variable must be included in the regression (Aiken et al., 1991). A significant and negative squared term indicates the inverted U-shaped relationship that I hypothesized in H2: community centralization is first associated with increased community longevity, but eventually it reaches a tipping point and becomes associated with *decreased* community longevity. Again, a significant squared term is not sufficient to establish a quadratic relationship (Lind & Mehlum, 2010), and so I thus confirm that the slope is sufficiently steep at both ends of the data. In **Table 7B** I calculate the margins at several points along the centralization distribution to show that the slope is significant at the 95% confidence interval. **Figures 8 – 11** depict graphically these margins plots and show that the turning point is located well within my data range. Taken together, these results suggest that overall, community centralization does exert a curvilinear effect on community longevity and thus Hypothesis 2 is supported at the 20 – 50% membership threshold models.

DISCUSSION

Online extremist groups pose a significant threat to the safety and well-being of citizens, societies, and social institutions around the world (Holt et al., 2020; Muthukrishna et al., 2017). Extant work indicates that such groups give rise to radicalization and violent behaviors (Bouchard & Nash, 2015; Gaudette et al., 2022) whose consequences reverberate across wide swaths of stakeholders. Given the high-stakes nature of the behavior that these groups can foment, researchers have called for more exploration of these types of organizational forms on the "fringes" of society, as well as the role of network relationships in proliferating their agendas (Greve, Palmer, et al., 2010; Palmer et al., 2016a; Greve et al., 2022). This paper offers one attempt to do so.

This study investigates the role of two key structural characteristics on the persistence of misconduct communities: social cohesion and structural inequality. I take a network community approach and locate communities of white supremacists in a large white supremacist online chat forum who post on the same threads together. Little is known about misconduct as a structural, organized phenomenon among multiple actors that evolves over time (Palmer & Moore, 2016). I offer a novel theoretical framework in which the persistence of community-based misconduct is a function not just of its overall social cohesion (its density) but also of the specific distribution of that cohesion (its centralization). I define community longevity as the number of contiguous years that a community maintains certain levels of membership. Using longitudinal data from 2002 – 2012, I find overall support for my hypotheses that social cohesion and structural inequality have inverted curvilinear relationships on community longevity. Taken together, this study expands our understanding of the structural underpinnings of how organized misconduct may persist over time.

In this study I define communities as significant meso-level structures between dyads and networks, whose interconnections are denser than in other regions of the network and thus create a pattern of tie formation that engenders relatively cohesive local structures (Thornton et al., 2012; Newman, 2016). Importing work that explore communities as institutional logics (Marquis & Battilana, 2009), I assert that misconduct communities embody regional social contexts with their own norms and monitoring capabilities, and that as such they are a meaningful driver of the persistence of misconduct. While communities are, by nature, more cohesive than other areas of a network, that cohesiveness still varies dramatically based on community structure (Marquis et al., 2007). In this study, I specifically explore the role of two types of social cohesion: density, or a community's overall level of social cohesion, which captures the amount of closure among within-community relationships, and centralization, which captures the specific tie distribution structure of a community and captures the extent to which this distribution is equal or unequal among community members. I argue that both of these constructs influence the extent to which communities can both enforce norms and monitor the behavior of members while still sufficiently flying under the radar of would-be interlopers who can cause real damage to these groups (Kalven, 2016; Potok, 2015; Schulte, 2022; Verini, 2023), and that the ability to do so has implications for how long a misconduct community persists

I hypothesized that density would be initially helpful for a community in this setting as it promotes norm strength and strong monitoring capabilities among members (Coleman, 1988; Granovetter, 1985), but would eventually become a liability, as denser communities are easier to disrupt that sparser ones (Baker & Faulkner, 2009; Everton & Cunningham, 2015; Morselli et al., 2007; Simmel, 1906). I next hypothesized that centralization would initially be positive for group survival as it improves group efficiency while lowering the risk of outsider detection, but that it would eventually become more difficult to operate as a unified group (Everton & Cunningham, 2015; Morselli et al., 2007), as the normative strength of the community would be weakened and the risk of member attrition would thus be higher (Shapiro, 2013; Greve, Baum, et al., 2010; Rowley et al., 2005). My results support this hypothesis at the 20 – 50% membership thresholds. My findings support these relationships and, taken together, suggest that these communities do operate as their own form of institutional environments and that moderate levels of density and centralization may best suit such communities' ongoing longevity.

There are a few limitations to this study that warrant mention. The first relates to the difficulty of acquiring complete network data, especially in a "dark" context in which secrecy is inherent (Wang et al., 2021). Thus, it is difficult to confirm that my dataset indeed reflects all relationships among white supremacists. Indeed, in the context of online extremist groups, many users "lurk" and may be ingesting content without posting themselves; in this case, these relationships would be missing from my data (Nielsen, 2009; Sudhakar et al., 2022). This is a common problem among most research that attempts to study misconduct (Baker & Faulkner, 1993; Cunningham et al., 2016; Morselli, 2009), but it nevertheless needs to be noted. Following work by Jain and colleagues (2022) I made a number of sampling decisions that maximize the likelihood of this data capturing meaningful social relationships that I believe mitigate the risks inherent to studying this topic.

Relatedly, an alternative explanation for the findings in my data is that only the particularly dysfunctional communities are so brazen about their behavior as to post repeatedly or blatantly on an online forum and that there are actually communities who, as density and / or centralization grow, become more functional and become better at conducting their business under the radar of hostile third-parties. If this were the case, the results showing the inverted curvilinear effect would in fact be missing the *linear* relationship such that as density / centralization increases, longevity increases as well. There are a few reasons to cast doubt on this possibility. First, as much research on so-called "dark" networks has demonstrated, even fully-illicit organizations such as drug rings (Bouchard, 2007; Calderoni, 2012), terrorist groups (Asal & Rethemeyer, 2008) or the Mafia (Agreste et al., 2016; DellaPosta, 2017) navigate tensions between social cohesion and structural inequality and often face repercussions for becoming too dense or too centralized. Thus, even in cases where such network structures have the highest incentive to remain as secret as possible, the tradeoffs I describe in my theorizing still apply. Additionally, network research demonstrates that most often, network community members have very little insight into the overall structure within which they are embedded (Burt, 2002; Friedkin, 1983). Thus, while members might have some understanding of how they fit structurally with their direct ties, a broader sense of community properties is likely to be very limited. Together, this suggests that the curvilinear effects demonstrated in this context are not likely to be missing a core quadrant of communities who simply become more intentional or better at hiding their behaviors; however, it is still a possibility that the "darkest" of network communities remain entirely off the grid and that, as such, we do not ever – or only are partially – aware of their behaviors over time (Milward, 2015).

Next, given the paucity of research on organized misconduct, there is very little existing guidance on establishing empirical measures of continuity. This paper represents one attempt to define misconduct persistence as based on shared membership over contiguous years, inspired by prior work in sociology (Vedres & Stark, 2010) and in organizational management research (Greve, Baum, et al., 2010; Rowley et al., 2005; Sytch & Tatarynowicz, 2014). I define shared membership as a percent of the community in year *t* and specify membership thresholds at the 10 – 50% levels. I expect my results are more conservative in part due to this contiguous definition; future work may benefit from exploring broader time specifications to see if communities may persist (i.e., four-year windows; see Rowley et al., 2005). My findings suggest that the membership thresholds do not meaningfully change the effect of my independent variables on community longevity above the 10% threshold. It is possible that community properties do not hold among groups with less than 10% continued membership year over year. Perhaps community members do not see themselves as members of a community with a lack of more historical context among members in the new community, and that, as such, monitoring or normative pressures are not particularly felt by community members. Perhaps higher levels of shared membership over time are needed given that these communities do not interact in-person and instead rely on online exchanges. To establish a stronger sense of normative pressures specifically in such an online context, it may be necessary to have higher levels of membership continuity over time.

Lastly, this study takes place in a long-running white supremacist chat forum in the United States. The stakes are incredibly high in such a setting: exposure to, and participation in, white supremacist online groups has been demonstrated to lead to an increase in harmful and violent behaviors in the real-world. I argue this makes it a particularly compelling context to examine the structural underpinnings of the persistence of misconduct, in part due to the availability of rich, longitudinal data, and in part due to the serious nature of the context. However, I note that my results may be somewhat limited in generalizability to more traditional organizational settings in which the misconduct is likely less severe. Indeed, in the context of most legitimized business environments, the threshold of tolerance for misconduct may be much lower and the concern of buffering outsider threats may be much higher. Nevertheless, this study fills a glaring gap in existing work by offering a wealth of rich, longitudinal data on misconduct that would be nearly impossible to replicate more traditional business settings (with notable exceptions including Brandy Aven's work with the Enron email corpus; see Aven, 2015). Generally, the reality of data (un)availability in attempting to study the topic of organized misconduct more broadly impedes systematic study of it (Wang et al., 2021). Thus, this study offers one attempt to uncover patterns of organized misconduct with an incredibly unique longitudinal dataset that can contribute to our understanding wrongdoing as an organized phenomenon.

CONCLUSION

The internet has enabled intimate connections to develop among people worldwide and has fundamentally changed the methods of organizing that are available to individuals. Unfortunately, this bourgeoning digital milieu has bolstered extremist groups online (Dalgaard-

Nielsen, 2010), and these groups promote radicalization and harmful behaviors in the real world (Bouchard & Nash, 2015; Colleoni et al., 2014).

Exploration on this topic in different organizational contexts would improve the robustness of this paper's theoretical framework and further generalize its findings. Organizational misconduct is an incredibly diverse phenomenon. Much scholarly work has explored different manifestations of this concept, focusing largely on atomized or socialized views of misconduct. While this is important work, more research is needed to understand misconduct as an *organized* phenomenon comprised of multiple actors. This paper takes a step forward in doing so.

In considering misconduct as a relational phenomenon, it behooves us to consider the relational aspects of these groups that contribute to their success in managing the tensions between security and efficiency over time. Some groups seem to clearly be better than others at perpetuating misconduct while mitigating outsider interference. In proposing a community-based theory of misconduct, I offer clear patterns that can help policy and organizational leaders better anticipate and interrupt organized misconduct by leveraging network data to identify these patterns. While we tend to consider misconduct as a phenomenon of bad apples, or of bad barrel cultures, my findings indicate that actually there are relational structures that reflect coordination patterns and establish pockets somewhere between the bad apple and bad barrel analyses. Exploring the structural attributes of groups engaging misconduct is a step towards understanding the fundamental question: "how do they get away with it for so long?" Thus, this paper contributes to organizational research by offering a novel theory of the persistence of misconduct over time and sets the groundwork for future research to further test and refine its findings.

FIGURES

Figure 4.1. Network structure of global network, 2008.

Bubbles correspond to different communities, proportional to number of members per community.

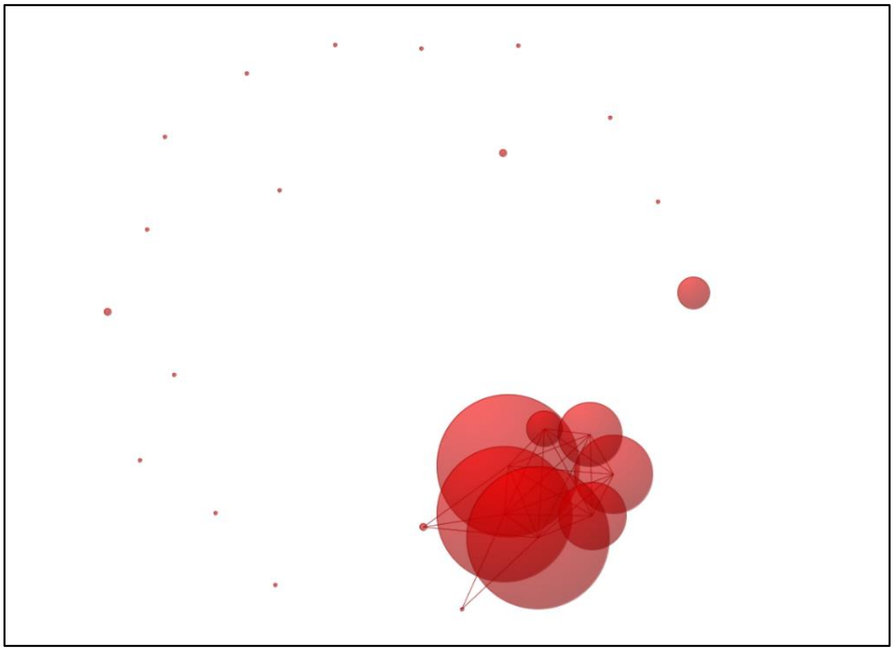


Figure 4.2. Network community structure of final sample, 2015.
Bubbles correspond to different communities, proportional to number of members per community.

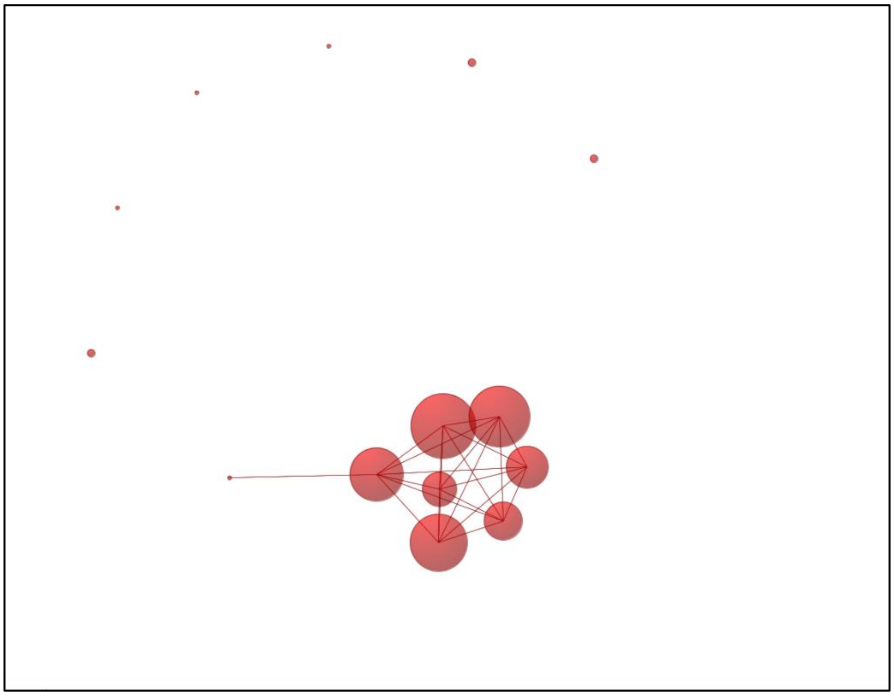


Figure 4.3. Relationship between community density and centralization.
X axis: community centralization; Y axis: community density

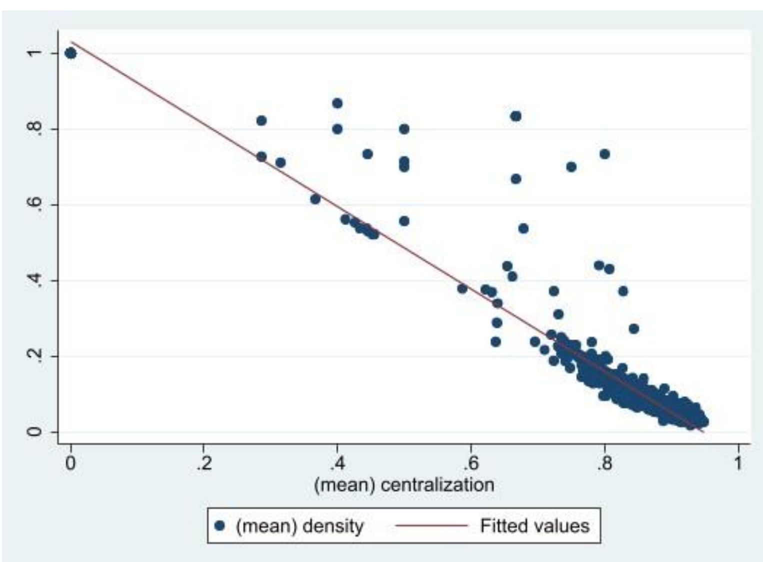


Figure 4.4. Relationship between community density and longevity, threshold 20%.

X axis: community density; Y axis: average community duration.

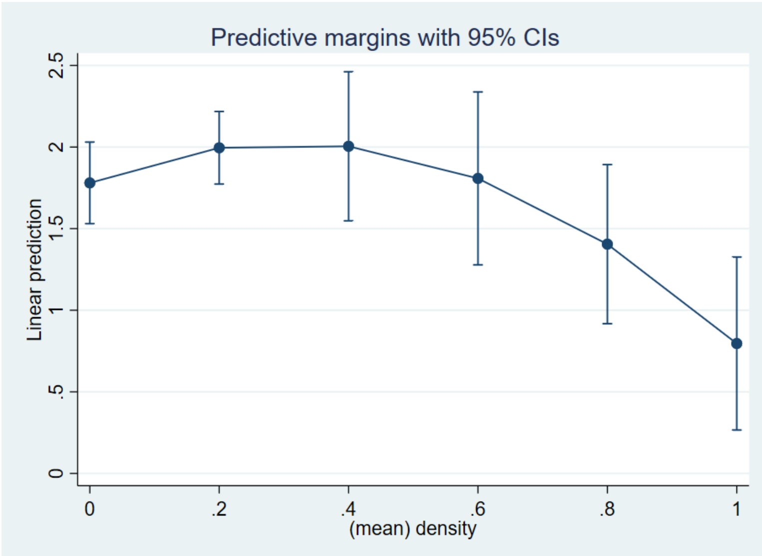


Figure 4.5. Relationship between community density and longevity, threshold 30%.
X axis: community density; Y axis: average community duration.

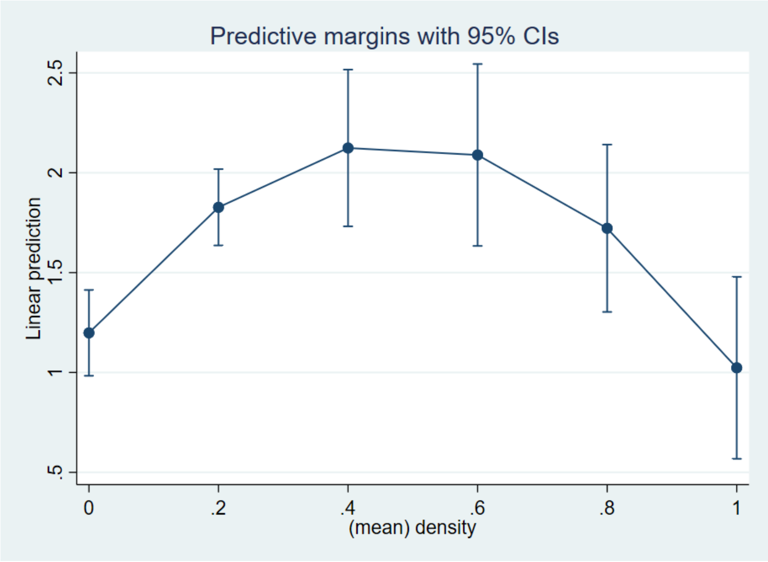


Figure 4.6. Relationship between community density and longevity, threshold 40%.
X axis: community density; Y axis: average community duration.

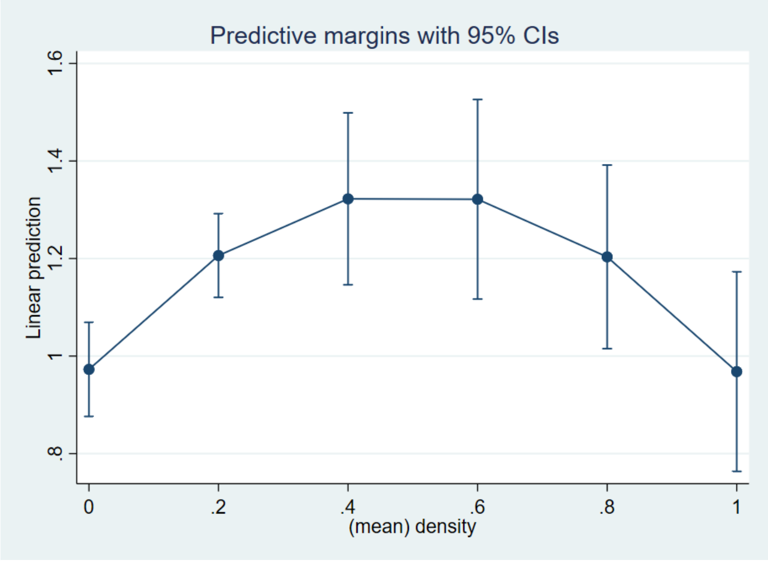


Figure 4.7. Relationship between community density and longevity, threshold 50%.
X axis: community density; Y axis: average community duration.

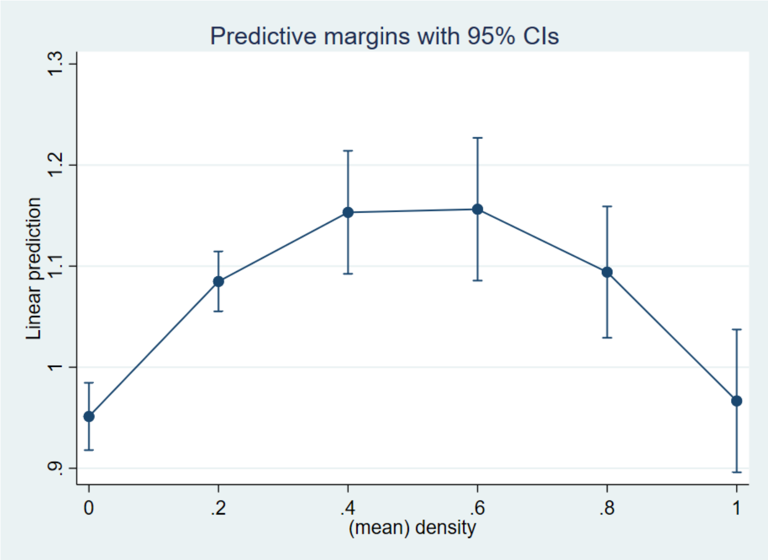


Figure 4.8. Relationship between community centralization and longevity, threshold 20%.
X axis: community centralization; Y axis: average community duration.

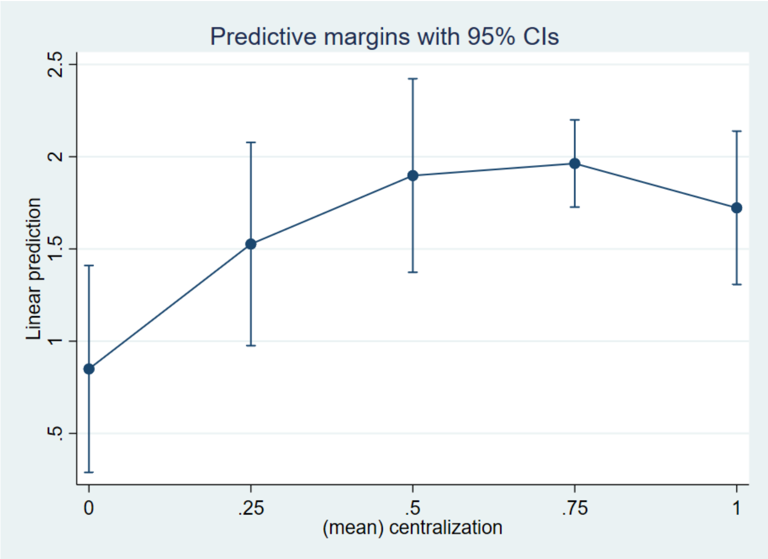


Figure 4.9. Relationship between community centralization and longevity, threshold 30%.
X axis: community centralization; Y axis: average community duration.

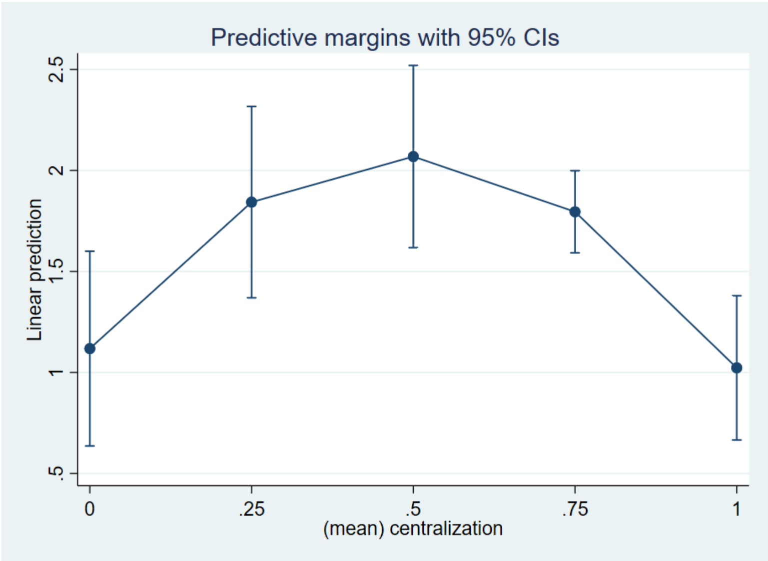


Figure 4.10. Relationship between community centralization and longevity, threshold 40%.
X axis: community centralization; Y axis: average community duration.

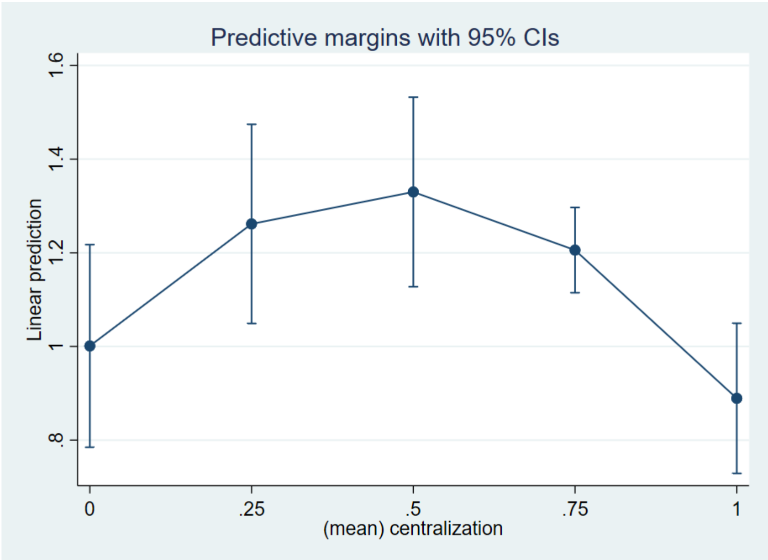
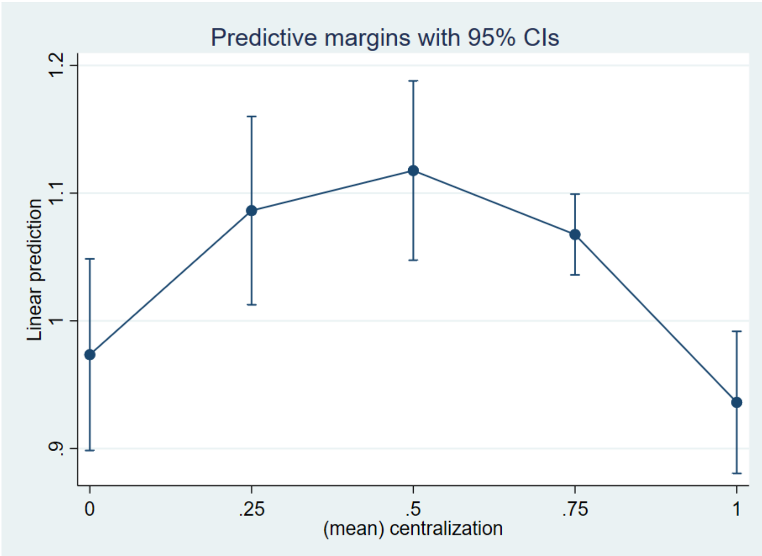


Figure 4.11. Relationship between community centralization and longevity, threshold 50%.
X axis: community centralization; Y axis: average community duration.



TABLES

Table 4.1. Summary statistics for all posts (global population).

Variable	Obs	Mean	Std. dev.	Min	Max
Members per thread (unique)	9,761,344	66.81	172.84	1	3,477
Member posts per thread	9,761,344	88.75	631.92	1	10,085
Posts per thread (overall)	9,761,344	757.10	3,244	1	36,225
Thread post date range (days)	9,761,344	514.84	1,183.21	0	6,923
Posts per member (overall)	9,761,344	7,025.82	14,838	1	98,286
Member post date range (days)	9,761,344	2,465	1,905	0	6,939
Threads per member	9,761,344	3,114	6,082	1	37,486
Year	9,761,344	2010	4.52	2002	2020
Average thread lasts approximately 1.40 years (514 days)					

Table 4.2. Summary statistics for all posts (global population), with sampling decisions.

Variable	Obs	Mean	Std. dev.	Min	Max
Members per thread (unique)	4,920,309	12.29	8.76	2	68
Member posts per thread	4,920,309	132.22	727.63	2	10,085
Posts per thread (overall)	4,920,309	679.59	2,677	4	25,193
Thread post date range (days)	4,920,309	533.90	1,140	0	6,758
Posts per member (overall)	4,920,309	5,578	11,654	2	66,598
Member post date range (days)	4,920,309	903.52	1,827	1	12,984
Threads per member	4,920,309	2,352	1,891	0	6,939
Year	4,920,309	2010.41	4.52	2002	2020
Newman modularity	19	0.28	0.10	0.13	0.42
Average thread lasts approximately 1.46 years (533 days)					

Table 4.3. Summary statistics for final sample, 2002 – 2012.

Variable	Obs	Mean	Std. dev.	Min	Max
Members per thread (unique)	261,345	8.49	6.92	2	47
Member posts per thread	261,345	3.88	5.88	2	741
Posts per thread (overall)	261,345	40.17	61.40	4	2,876
Thread post date range (days)	261,345	203.60	591.57	0	6,758
Posts per member (overall)	261,345	1,993	4,913	2	60,251
Member post date range (days)	261,345	1,657	1,672	0	6,939
Threads per member	261,345	457.94	1,097	1	12,873
Total threads per community	261,345	2,014	1,354	1	5,524
Year	261,345	2006	3.16	2002	2012
Newman modularity	11	0.59	0.14	0.33	0.75
Community size	1,002	316.99	179.42	2	954
Average thread lasts approximately 0.56 years (203 days)					

Table 4.4. Final sample distribution of communities, threads, and members, 2002 – 2012.

Year	Communities	Threads	Members	Newman Modularity
2002	159	6,657	1,982	0.326
2003	155	8,440	1,934	0.410
2004	142	10,921	2,509	0.430
2005	136	9,322	2,109	0.610
2006	118	7,572	1,738	0.629
2007	87	5,652	1,184	0.644
2008	66	4,753	855	0.650
2009	62	5,193	1,138	0.654
2010	39	6,065	893	0.708
2011	24	4,292	601	0.721
2012	14	5,609	1,013	0.752
Total	**1,002**	**74,476**	**15,956**	**-**
Average	91.09	6,771	1,491	0.594

Table 4.5A. Summary statistics for dependent, independent, and control variables.

Variable	Obs	Mean	Med	Std.	Min	Max
(1) Community density	1,002	0.14	0.09	0.20	0.02	1
(2) Community centralization	1,002	0.82	0.86	0.18	0	0.95
(3) Community structural holes	1,002	47.43	41.95	26.65	1	174
(4) Community size	1,002	316	294	179	2	954
(5) Community size *(logged)*	1,002	5.33	5.56	1.13	0.69	6.86
(6) Community density *(at found)*	1,002	0.14	0.07	0.21	0.02	1
(7) Community centralization *(at found)*	1,002	0.82	0.88	0.19	0	0.95
(8) Community structural holes *(at found)*	1,002	49.19	39.18	34.77	1	174
(8) Community died *(dummy)*	988	0.94	1	0.23	0	1
(9) Year	1,002	2005	2005	2.59	2002	2012
(10) Community duration						
10% membership	1,002	2.10	1	1.73	1	10
20% membership	1,002	1.84	1	1.63	1	10
30% membership	1,002	1.51	1	1.36	1	10
40% membership	1,002	1.09	1	0.59	1	9
50% membership	1,002	1.02	1	0.20	1	4

Table 4.5B. Correlation matrix for dependent, independent, and control variables.

Vars	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	1										
(2)	-0.963***	1									
(3)	-0.476***	0.495***	1								
(4)	-0.557***	0.565***	0.702***	1							
(5)	-0.946***	0.902***	0.648***	0.755***	1						
(6)	0.946***	-0.904***	-0.448***	-0.513***	-0.895***	1					
(7)	-0.913***	0.943***	0.475***	0.521***	0.856***	-0.957***	1				
(8)	-0.382***	0.391***	0.768***	0.547***	0.517***	-0.412***	0.452***	1			
(9)	0.003	0.015	-0.011	0.124***	-0.002	0.016	-0.004	0.001	1		
(10)	0.333***	-0.337***	-0.374***	-0.518***	-0.386***	0.328***	-0.334***	-0.269***	-0.335***	1	
(11)	-0.292***	0.264***	0.152***	0.109***	0.287***	-0.305***	0.296***	0.201***	-0.259***	-0.297***	1
**** p<0.01, ** p<0.05, * p<0.1*											

Table 4.6A. Results at shared membership thresholds 10% & 20%.

	10% Shared Membership Threshold				20% Shared Membership Threshold			
VARIABLES	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Density	**-1.222*** **	0.764			**-1.112*** **	1.591		
	(0.329)	(1.460)			(0.304)	(1.346)		
Density squared		-1.892				**-2.576** **		
		(1.355)				(1.250)		
Centralization			**1.301*** **	**2.745** **			**1.183*** **	**3.320*** **
			(0.372)	(1.371)			(0.343)	(1.265)
Centralization squared				-1.654				**-2.447* **
				(1.511)				(1.394)
Community size	-0.00171***	-0.00143***	-0.00168***	-0.00140***	-0.00205***	-0.00167***	-0.00203***	-0.00161***
	(0.000389)	(0.000438)	(0.000391)	(0.000467)	(0.000359)	(0.000404)	(0.000361)	(0.000430)
Community died *(dummy)*	-2.380***	-2.353***	-2.409***	-2.382***	-2.318***	-2.281***	-2.344***	-2.304***
	(0.233)	(0.233)	(0.232)	(0.233)	(0.215)	(0.215)	(0.214)	(0.215)
Constant	5.054***	4.770***	3.837***	3.697***	4.837***	4.450***	3.729***	3.523***
	(0.263)	(0.332)	(0.363)	(0.385)	(0.243)	(0.306)	(0.335)	(0.355)
Observations	988	988	988	988	988	988	988	988
R-squared	0.151	0.153	0.150	0.151	0.185	0.188	0.183	0.186
Yearly FE	Y	Y	Y	Y	Y	Y	Y	Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.6B. Results at shared membership thresholds 30% & 40%.

	30% Shared Membership Threshold				40% Shared Membership Threshold			
VARIABLES	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Density	-0.381	**3.974*****			-0.0773	**1.460*****		
	(0.263)	(1.157)			(0.118)	(0.520)		
Density squared		**-4.149*****				**-1.465*****		
		(1.074)				(0.482)		
Centralization			0.410	**3.899*****			0.0829	**1.427*****
			(0.297)	(1.088)			(0.133)	(0.488)
Centralization squared				**-3.994*****				**-1.539*****
				(1.198)				(0.538)
Community size	-0.00105***	-0.000434	-0.00105***	-0.000371	-0.000293**	-7.47e-05	-0.000292**	-3.19e-05
	(0.000310)	(0.000347)	(0.000312)	(0.000370)	(0.000139)	(0.000156)	(0.000140)	(0.000166)
Community died *(dummy)*	-1.934***	-1.874***	-1.943***	-1.877***	-0.371***	-0.350***	-0.373***	-0.348***
	(0.186)	(0.185)	(0.185)	(0.185)	(0.0831)	(0.0831)	(0.0829)	(0.0830)
Constant	3.714***	3.091***	3.331***	2.994***	1.544***	1.324***	1.467***	1.337***
	(0.210)	(0.263)	(0.289)	(0.305)	(0.0939)	(0.118)	(0.130)	(0.137)
Observations	988	988	988	988	988	988	988	988
R-squared	0.132	0.146	0.132	0.142	0.069	0.078	0.069	0.077
Yearly FE	Y	Y	Y	Y	Y	Y	Y	Y

Table 4.6C. Results at shared membership threshold 50%.

	50% Shared Membership Threshold			
VARIABLES	(1)	(2)	(3)	(4)
Density	-0.0251	**0.831*****		
	(0.0409)	(0.179)		
Density squared		**-0.816*****		
		(0.167)		
Centralization			0.0450	**0.614*****
			(0.0462)	(0.169)
Centralization squared				**-0.651*****
				(0.187)
Community size	-0.000104**	1.76e-05	-0.000113**	-3.31e-06
	(4.83e-05)	(5.39e-05)	(4.85e-05)	(5.76e-05)
Community died *(dummy)*	-0.0196	-0.00776	-0.0190	-0.00834
	(0.0289)	(0.0287)	(0.0288)	(0.0288)
Constant	1.075***	0.953***	1.037***	0.982***
	(0.0327)	(0.0408)	(0.0451)	(0.0475)
Observations	988	988	988	988
R-squared	0.062	0.085	0.063	0.074
Yearly FE	Y	Y	Y	Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.7A. Density distribution margins for all shared membership models.

VARIABLES	20%	30%	40%	50%
1. Margins at density = 0	**1.780*** **	**1.198*** **	**0.973*** **	**0.951*** **
	(0.128)	(0.110)	(0.0492)	(0.0170)
2. Margins at density = 0.2	**1.996*** **	**1.827*** **	**1.206*** **	**1.085*** **
	(0.113)	(0.0975)	(0.0438)	(0.0151)
3. Margins at density = 0.4	**2.005*** **	**2.124*** **	**1.322*** **	**1.153*** **
	(0.233)	(0.200)	(0.0900)	(0.0310)
4. Margins at density = 0.6	**1.808*** **	**2.089*** **	**1.322*** **	**1.156*** **
	(0.270)	(0.232)	(0.104)	(0.0360)
5. Margins at density = 0.8	**1.405*** **	**1.722*** **	**1.203*** **	**1.094*** **
	(0.249)	(0.214)	(0.0960)	(0.0331)
6. Margins at density = 1	**0.796*** **	**1.023*** **	**0.968*** **	**0.967*** **
	(0.270)	(0.232)	(0.104)	(0.0360)
Observations	988	988	988	988

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.7B. Centralization distribution margins for all shared membership models.

VARIABLES	20%	30%	40%	50%
1. Margins at centralization = 0	**0.849*** **	**1.118*** **	**1.001*** **	**0.974*** **
	(0.286)	(0.246)	(0.110)	(0.0383)
2. Margins at centralization = 0.25	**1.527*** **	**1.843*** **	**1.262*** **	**1.086*** **
	(0.281)	(0.242)	(0.108)	(0.0376)
3. Margins at centralization = 0.50	**1.898*** **	**2.069*** **	**1.330*** **	**1.118*** **
	(0.268)	(0.230)	(0.103)	(0.0358)
4. Margins at centralization = 0.75	**1.963*** **	**1.795*** **	**1.206*** **	**1.068*** **
	(0.120)	(0.104)	(0.0465)	(0.0161)
5. Margins at centralization = 1.0	**1.723*** **	**1.023*** **	**0.889*** **	**0.936*** **
	(0.212)	(0.182)	(0.0818)	(0.0284)
Observations	988	988	988	988

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix C: Cox Proportional Hazards Model Results

Table C1. Cox Proportional Hazards Model results, full sample 10 – 30%.

VARIABLES	10%				20%				30%			
Density	**2.129*** **	0.808			**1.880*** **	**0.499***			**1.401*** **	**0.300*** **		
	(0.133)	(0.346)			(0.101)	(0.194)			(0.0549)	(0.0901)		
Density squared		**2.475** **				**3.463*** **				**4.272*** **		
		(0.931)				(1.186)				(1.154)		
Centralization			**0.465*** **	**0.183*** **			**0.532*** **	**0.143*** **			**0.716*** **	**0.177*** **
			(0.0302)	(0.0674)			(0.0295)	(0.0478)			(0.0285)	(0.0460)
Centralization squared				**2.998** **				**4.714*** **				**5.106*** **
				(1.368)				(1.942)				(1.593)
Community size	1.001***	1.000***	1.000***	1.000*	1.001***	1.000***	1.001***	1.000***	1.000***	1.000***	1.000***	1.000*
	(0.000113)	(0.000131)	(0.000114)	(0.000144)	(9.15e-05)	(0.000108)	(9.19e-05)	(0.000118)	(6.55e-05)	(7.45e-05)	(6.45e-05)	(7.90e-05)
Observations	1,002	1,002	1,002	1,002	1,002	1,002	1,002	1,002	1,002	1,002	1,002	1,002

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table C2. Cox Proportional Hazards Model results, full sample 40 & 50%.

VARIABLES	40%				50%			
Density	**1.052*** **	**0.562*** **			1.008	**0.637** **		
	(0.0147)	(0.101)			(0.0121)	(0.115)		
Density squared		**1.812*** **				**1.545*** **		
		(0.304)				(0.256)		
Centralization			**0.957*** **	**0.526*** **			0.986	**0.727*** **
			(0.0126)	(0.0740)			(0.0110)	(0.0850)
Centralization squared				**2.000*** **				**1.423** **
				(0.326)				(0.196)
Community size	1.000***	1.000	1.000***	1.000	1.000***	1.000	1.000***	1.000
	(2.29e-05)	(2.60e-05)	(2.24e-05)	(2.56e-05)	(1.93e-05)	(2.68e-05)	(1.91e-05)	(2.30e-05)
Observations	1,002	1,002	1,002	1,002	1,002	1,002	1,002	1,002

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix D: Structural Holes as Community Fragmentation

Table B1. Results at shared membership threshold, thresholds 10% – 30 %.

	10% Shared Membership Threshold			20% Shared Membership Threshold			30% Shared Membership Threshold		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Density			-0.272			0.176			**2.599****
			(1.452)			(1.318)			(1.123)
Density squared			0.0224			-0.208			**-1.961***
			(1.380)			(1.253)			(1.068)
Structural holes	**0.0138*****	**0.0447*****	**0.0416*****	**0.0192*****	**0.0480*****	**0.0472*****	**0.0188*****	**0.0368*****	**0.0415*****
	(0.00275)	(0.00723)	(0.00899)	(0.00250)	(0.00656)	(0.00816)	(0.00213)	(0.00561)	(0.00696)
Structural holes squared		**-0.000220*****	**-0.000200*****		**-0.000205*****	**-0.000200*****		**0.000128*****	**-0.000161*****
		(4.76e-05)	(5.82e-05)		(4.32e-05)	(5.29e-05)		(3.70e-05)	(4.51e-05)
Community size	-0.00237***	-0.00312***	-0.00317***	-0.00333***	-0.00402***	-0.00399***	-0.00273***	-0.00316***	-0.00266***
	(0.000435)	(0.000459)	(0.000538)	(0.000395)	(0.000417)	(0.000488)	(0.000336)	(0.000357)	(0.000416)
Community died *(dummy)*	-2.342***	-2.146***	-2.145***	-2.213***	-2.030***	-2.029***	-1.768***	-1.654***	-1.644***
	(0.231)	(0.233)	(0.233)	(0.210)	(0.211)	(0.212)	(0.179)	(0.181)	(0.180)
Constant	4.406***	3.639***	3.780***	4.078***	3.364***	3.361***	3.143***	2.696***	2.155***
	(0.258)	(0.305)	(0.401)	(0.235)	(0.277)	(0.364)	(0.200)	(0.237)	(0.310)
Observations	988	988	988	988	988	988	988	988	988
R-squared	0.161	0.179	0.179	0.221	0.238	0.238	0.195	0.205	0.211

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B2. Results at shared membership threshold, thresholds 40% & 50%.

	40% Shared Membership Threshold			50% Shared Membership Threshold		
VARIABLES	(10)	(11)	(12)	(13)	(14)	(15
Density			**1.248****			**0.821*****
			(0.521)			(0.181)
Density squared			**-0.989****			**-0.798*****
			(0.496)			(0.172)
Structural holes	**0.00263*****	**0.0102*****	**0.0117*****	0.000420	0.00145	0.000391
	(0.000985)	(0.00260)	(0.00323)	(0.000344)	(0.000912)	(0.00112)
Structural holes squared		**-5.38e-05*****	**-6.54e-05*****		-7.31e-06	-1.85e-06
		(1.72e-05)	(2.09e-05)		(6.01e-06)	(7.27e-06)
Community size	-0.000513***	-0.000695***	-0.000454**	-0.000132**	-0.000156***	8.56e-07
	(0.000156)	(0.000166)	(0.000193)	(5.43e-05)	(5.80e-05)	(6.71e-05)
Community died *(dummy)*	-0.350***	-0.302***	-0.297***	-0.0173	-0.0108	-0.00580
	(0.0829)	(0.0839)	(0.0837)	(0.0289)	(0.0294)	(0.0291)
Constant	1.458***	1.271***	1.032***	1.059***	1.033***	0.944***
	(0.0926)	(0.110)	(0.144)	(0.0323)	(0.0385)	(0.0500)
Observations	988	988	988	988	988	988
R-squared	0.076	0.085	0.091	0.063	0.065	0.085

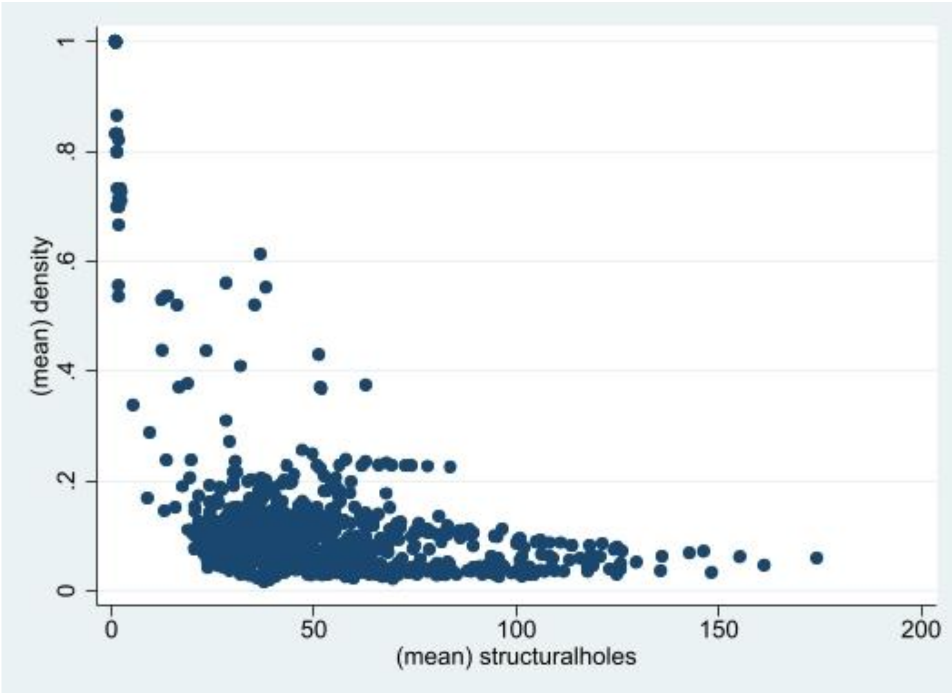
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B3. Structural holes distribution margins for all shared membership thresholds.

VARIABLES	10%	20%	30%	40%	50%
1. Margins at structural holes = 20	**1.438*****	**1.052*****	**0.822*****	**0.948*****	**0.999*****
	(0.111)	(0.100)	(0.0859)	(0.0399)	(0.0140)
2. Margins at structural holes = 40	**2.067*****	**1.766*****	**1.404*****	**1.087*****	**1.019*****
	(0.0564)	(0.0512)	(0.0438)	(0.0203)	(0.00712)
3. Margins at structural holes = 60	**2.521*****	**2.316*****	**1.885*****	**1.183*****	**1.033*****
	(0.0799)	(0.0725)	(0.0621)	(0.0288)	(0.0101)
4. Margins at structural holes = 80	**2.799*****	**2.701*****	**2.262*****	**1.237*****	**1.042*****
	(0.114)	(0.104)	(0.0886)	(0.0411)	(0.0144)
5. Margins at structural holes = 100	**2.901*****	**2.923*****	**2.538*****	**1.247*****	**1.045*****
	(0.152)	(0.138)	(0.118)	(0.0546)	(0.0191)
Observations	988	988	988	988	988

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure B1. Relationship between community density and structural holes.
X axis: community structural holes; Y axis, community density



Appendix E: Analyses on Thread Severity > 0.5

Note: These are threads with a toxicity score of 0.5 or higher. The toxicity scoring leverages Google's Counter Abuse Technology's API called "Perspective." This API calculates the probability that any given post is considered severely toxic; posts with a toxicity score of 0.5 are likely to be considered highly hateful, aggressive, and / or disrespectful. Results are robust to this subset of Whitestorm's threads.

Table E1. Results at shared membership thresholds 10 – 30%.

	10% Shared Membership Threshold				20% Shared Membership Threshold				30% Shared Membership Threshold			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Density	0.371	**2.707*** **			0.107	**0.814***			0.156**	**0.563*** **		
	(0.329)	(0.928)			(0.154)	(0.433)			(0.0694)	(0.195)		
Density squared		**-2.116*** **				**-0.641***				**-0.369** **		
		(0.786)				(0.367)				(0.166)		
Centralization			-0.284	**1.519***			0.0359	0.285			-0.117*	0.164
			(0.308)	(0.844)			(0.144)	(0.394)			(0.0650)	(0.178)
Centralization squared				**-2.005** **				-0.277				**-0.313***
				(0.874)				(0.408)				(0.184)
Community size	0.0118**	0.0163***	0.00999***	0.0117***	0.00166	0.00303	0.000229	0.000465	-0.000100	0.000688	-0.000862	-0.000597
	(0.00465)	(0.00494)	(0.00386)	(0.00393)	(0.00217)	(0.00230)	(0.00180)	(0.00183)	(0.000980)	(0.00104)	(0.000814)	(0.000828)
Community died *(dummy)*	-1.378***	-1.351***	-1.376***	-1.357***	-0.233***	-0.224***	-0.230***	-0.227***	0.00293	0.00771	0.00385	0.00682
	(0.112)	(0.112)	(0.112)	(0.112)	(0.0523)	(0.0524)	(0.0522)	(0.0524)	(0.0236)	(0.0237)	(0.0236)	(0.0237)
Constant	2.200***	1.521***	2.562***	2.174***	1.210***	1.004***	1.271***	1.218***	0.974***	0.856***	1.125***	1.065***
	(0.273)	(0.371)	(0.185)	(0.250)	(0.127)	(0.173)	(0.0862)	(0.117)	(0.0575)	(0.0782)	(0.0390)	(0.0528)
Observations	1,728	1,728	1,728	1,728	1,728	1,728	1,728	1,728	1,728	1,728	1,728	1,728
R-squared	0.106	0.109	0.105	0.108	0.060	0.062	0.060	0.060	0.023	0.026	0.022	0.024

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E2. Results at shared membership thresholds 40% & 50%.

	40% Shared Membership Threshold				50% Shared Membership Threshold			
VARIABLES	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Density	0.0310	**0.179****			**0.0463***	**0.179*****		
	(0.0273)	(0.0769)			(0.0238)	(0.0670)		
Density squared		**-0.134****				**-0.120****		
		(0.0651)				(0.0568)		
Centralization			-0.0205	0.0890			**-0.0381***	0.0832
			(0.0255)	(0.0700)			(0.0223)	(0.0610)
Centralization squared				**-0.122***				**-0.135****
				(0.0725)				(0.0631)
Community size	1.09e-05	0.000297	-0.000162	-5.89e-05	0.000152	0.000409	-4.80e-05	6.65e-05
	(0.000385)	(0.000409)	(0.000320)	(0.000326)	(0.000336)	(0.000357)	(0.000279)	(0.000284)
Community died *(dummy)*	0.000898	0.00263	0.00114	0.00229	0.000322	0.00188	0.000533	0.00182
	(0.00928)	(0.00931)	(0.00928)	(0.00930)	(0.00809)	(0.00812)	(0.00809)	(0.00811)
Constant	0.994***	0.951***	1.023***	1.000***	0.983***	0.944***	1.029***	1.003***
	(0.0226)	(0.0308)	(0.0153)	(0.0208)	(0.0197)	(0.0268)	(0.0134)	(0.0181)
Observations	1,728	1,728	1,728	1,728	1,728	1,728	1,728	1,728
R-squared	0.032	0.034	0.032	0.033	0.020	0.022	0.019	0.022

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E3. Structural holes: Results at shared membership thresholds 10 – 30%.

	10% Shared Membership Threshold		20% Shared Membership Threshold		30% Shared Membership Threshold	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Structural holes	0.0239	0.133	-0.0107	0.0532	-0.00594	-0.00146
	(0.0277)	(0.116)	(0.0129)	(0.0539)	(0.00583)	(0.0244)
Structural holes squared		-0.0124		-0.00727		-0.000509
		(0.0128)		(0.00594)		(0.00269)
Community size	0.00662**	0.00497	0.00103	5.95e-05	-0.00149**	-0.00156**
	(0.00330)	(0.00371)	(0.00154)	(0.00173)	(0.000695)	(0.000783)
Community died *(dummy)*	-1.366***	-1.344***	-0.233***	-0.220***	0.00484	0.00574
	(0.112)	(0.114)	(0.0522)	(0.0533)	(0.0236)	(0.0241)
Constant	2.403***	2.227***	1.310***	1.207***	1.097***	1.090***
	(0.162)	(0.242)	(0.0753)	(0.113)	(0.0341)	(0.0511)
Observations	1,728	1,728	1,728	1,728	1,728	1,728
R-squared	0.105	0.106	0.060	0.061	0.021	0.021

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E4. Structural holes: Results at shared membership thresholds 40% & 50%.

VARIABLES	40% Shared Membership Threshold (7)	(8)	50% Shared Membership Threshold (9)	(10)
Structural holes	-0.00190	-0.00830	-0.00184	-0.0108
	(0.00229)	(0.00958)	(0.00200)	(0.00835)
Structural holes squared		0.000727		0.00102
		(0.00106)		(0.000921)
Community size	-0.000231	-0.000134	-0.000258	-0.000122
	(0.000273)	(0.000307)	(0.000238)	(0.000268)
Community died *(dummy)*	0.00113	-0.000157	0.000874	-0.000926
	(0.00928)	(0.00947)	(0.00810)	(0.00826)
Constant	1.020***	1.031***	1.019***	1.034***
	(0.0134)	(0.0201)	(0.0117)	(0.0175)
Observations	1,728	1,728	1,728	1,728
R-squared	0.032	0.032	0.018	0.019

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E5. Density distribution margins for all shared membership models.

VARIABLES	10%	20%	30%	40%	50%
1. Margins at density = 0.2	**1.352*** **	**1.049*** **	**0.985*** **	**0.994*** **	**0.991*** **
	(0.0694)	(0.0324)	(0.0146)	(0.00575)	(0.00501)
2. Margins at density = 0.4	**1.640*** **	**1.135*** **	**1.053*** **	**1.014*** **	**1.013*** **
	(0.0522)	(0.0244)	(0.0110)	(0.00433)	(0.00377)
3. Margins at density = 0.6	**1.758*** **	**1.169*** **	**1.092*** **	**1.023*** **	**1.024*** **
	(0.106)	(0.0493)	(0.0223)	(0.00876)	(0.00763)
4. Margins at density = 0.8	**1.707*** **	**1.152*** **	**1.101*** **	**1.021*** **	**1.026*** **
	(0.155)	(0.0722)	(0.0326)	(0.0128)	(0.0112)
5. Margins at density = 1.0	**1.487*** **	**1.084*** **	**1.081*** **	**1.009*** **	**1.019*** **
	(0.242)	(0.113)	(0.0511)	(0.0201)	(0.0175)
Observations	1,728	1,728	1,728	1,728	1,728

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E5. Centralization distribution margins for all shared membership models.

VARIABLES	10%	20%	30%	40%	50%
1. Margins at centralization = 0	**1.381*** **	**1.033*** **	**1.050*** **	**1.000*** **	**1.007*** **
	(0.236)	(0.110)	(0.0497)	(0.0195)	(0.0170)
2. Margins at centralization = 0.2	**1.605*** **	**1.078*** **	**1.070*** **	**1.012*** **	**1.018*** **
	(0.133)	(0.0621)	(0.0281)	(0.0110)	(0.00961)
3. Margins at centralization = 0.4	**1.668*** **	**1.102*** **	**1.065*** **	**1.016*** **	**1.018*** **
	(0.0835)	(0.0390)	(0.0176)	(0.00692)	(0.00603)
4. Margins at centralization = 0.6	**1.571*** **	**1.104*** **	**1.036*** **	**1.009*** **	**1.008*** **
	(0.0378)	(0.0176)	(0.00797)	(0.00313)	(0.00273)
5. Margins at centralization = 0.8	**1.313*** **	**1.083*** **	**0.981*** **	**0.993*** **	**0.987*** **
	(0.0923)	(0.0431)	(0.0195)	(0.00765)	(0.00667)
Observations	1,728	1,728	1,728	1,728	1,728

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E6. Structural distribution margins for all shared membership models.

VARIABLES	10%	20%	30%	40%	50%
1. Margins at structural holes = 1	**1.331*** **	**1.060*** **	**1.038*** **	**1.018*** **	**1.019*** **
	(0.148)	(0.0689)	(0.0312)	(0.0123)	(0.0107)
2. Margins at structural holes = 3	**1.498*** **	**1.108*** **	**1.031*** **	**1.007*** **	**1.006*** **
	(0.0393)	(0.0183)	(0.00829)	(0.00326)	(0.00284)
3. Margins at structural holes = 5	**1.566*** **	**1.098*** **	**1.020*** **	**1.002*** **	**1.000*** **
	(0.0491)	(0.0229)	(0.0103)	(0.00406)	(0.00355)
4. Margins at structural holes = 7	**1.534*** **	**1.030*** **	**1.005*** **	**1.003*** **	**1.003*** **
	(0.109)	(0.0509)	(0.0231)	(0.00906)	(0.00790)
5. Margins at structural holes = 9	**1.403*** **	**0.904*** **	**0.986*** **	**1.010*** **	**1.014*** **
	(0.283)	(0.132)	(0.0597)	(0.0234)	(0.0205)
Observations	1,728	1,728	1,728	1,728	1,728

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E7. Cox Proportional Hazards Model results, SEVERE sample 10 – 30%.

VARIABLES	10%				20%				30%			
Density	0.978	**0.237*** **			0.999	**0.733** **			**0.926***	**0.780*** **		
	(0.0823)	(0.0657)			(0.0472)	(0.0911)			(0.0383)	(0.0688)		
Density squared		**3.591*** **				**1.325*** **				**1.170** **		
		(0.737)				(0.127)				(0.0787)		
Centralization			**0.963**	**0.351*** **			**0.935**	**0.855***			**1.051**	**0.944**
			(0.0766)	(0.0569)			(0.0419)	(0.0743)			(0.0432)	(0.0658)
Centralization squared				**3.073*** **				**1.104**				**1.125***
				(0.681)				(0.111)				(0.0799)
Community size	0.998**	0.995***	0.998**	0.997***	1.002***	1.001*	1.002***	1.002***	1.001	1.000	1.001***	1.001**
	(0.00118)	(0.00130)	(0.000961)	(0.000986)	(0.000590)	(0.000592)	(0.000525)	(0.000518)	(0.000394)	(0.000415)	(0.000365)	(0.000366)
Observations	1,736	1,736	1,736	1,736	1,736	1,736	1,736	1,736	1,736	1,736	1,736	1,736

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E8. Cox Proportional Hazards Model results, SEVERE sample 40 & 50%.

VARIABLES	40%				50%			
Density	0.981	**0.917***			**0.975***	**0.918***		
	(0.0142)	(0.0476)			(0.0128)	(0.0434)		
Density squared		**1.063***				**1.056**		
		(0.0385)				(0.0354)		
Centralization			1.009	0.966			1.018	**0.965***
			(0.0146)	(0.0241)			(0.0133)	(0.0200)
Centralization squared				1.050				**1.061***
				(0.0398)				(0.0330)
Community size	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	(0.000116)	(0.000169)	(0.000141)	(0.000147)	(8.49e-05)	(0.000142)	(0.000117)	(0.000120)
Observations	1,736	1,736	1,736	1,736	1,736	1,736	1,736	1,736

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure E1. Relationship between community density and longevity, threshold 10%.
X axis: community density; Y axis: average community duration.

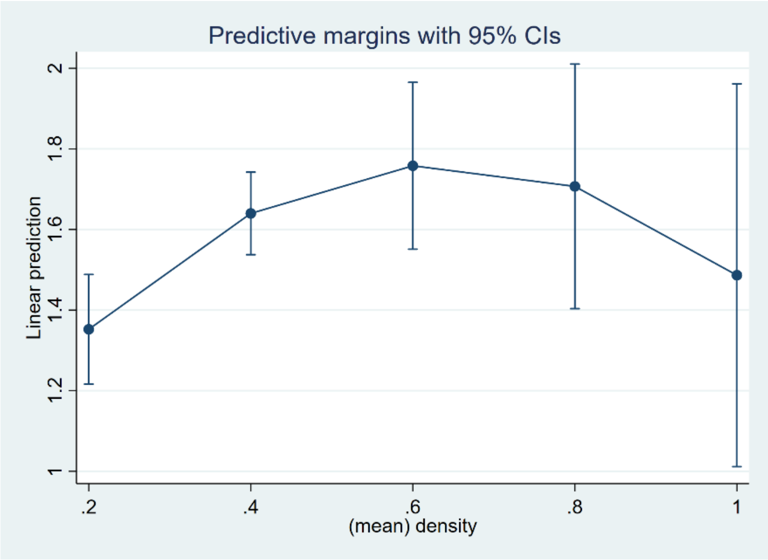


Figure E2. Relationship between community density and longevity, threshold 20%.
X axis: community density; Y axis: average community duration.

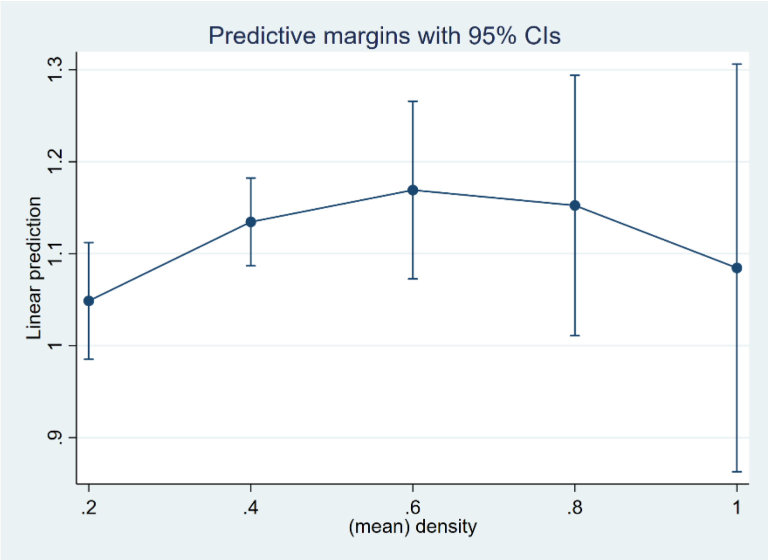


Figure E3. Relationship between community density and longevity, threshold 30%.
X axis: community density; Y axis: average community duration.

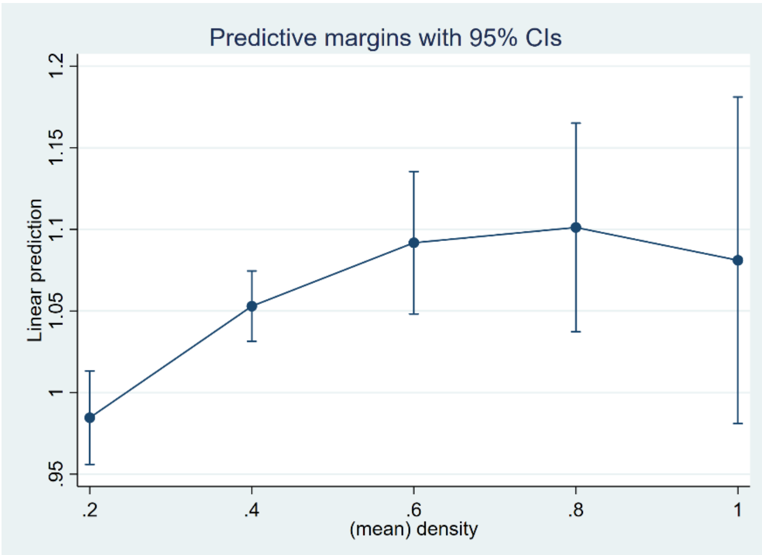


Figure E4. Relationship between community density and longevity, threshold 40%.
X axis: community density; Y axis: average community duration.

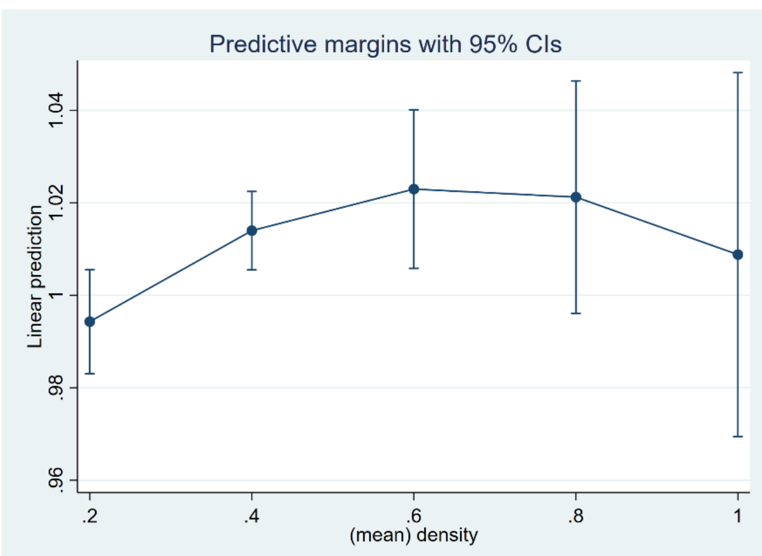


Figure E5. Relationship between community density and longevity, threshold 50%.

X axis: community density; Y axis: average community duration.

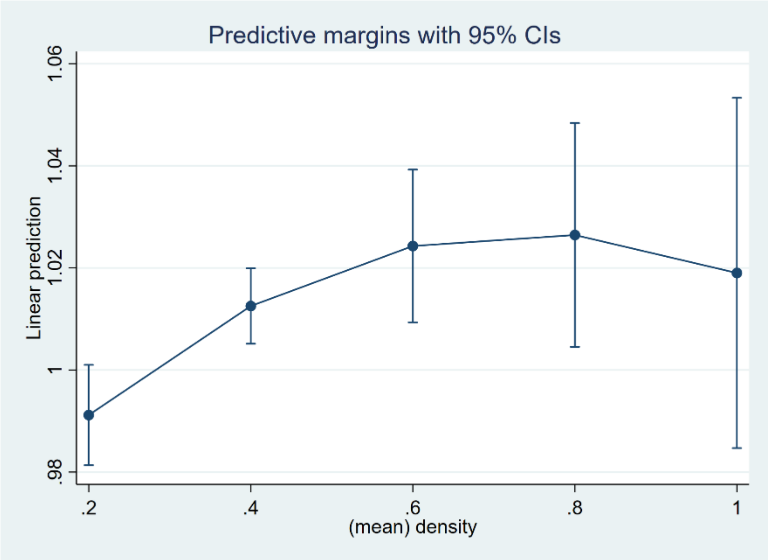


Figure E6. Relationship between community centralization and longevity, threshold 10%.

X axis: community centralization; Y axis: average community duration.

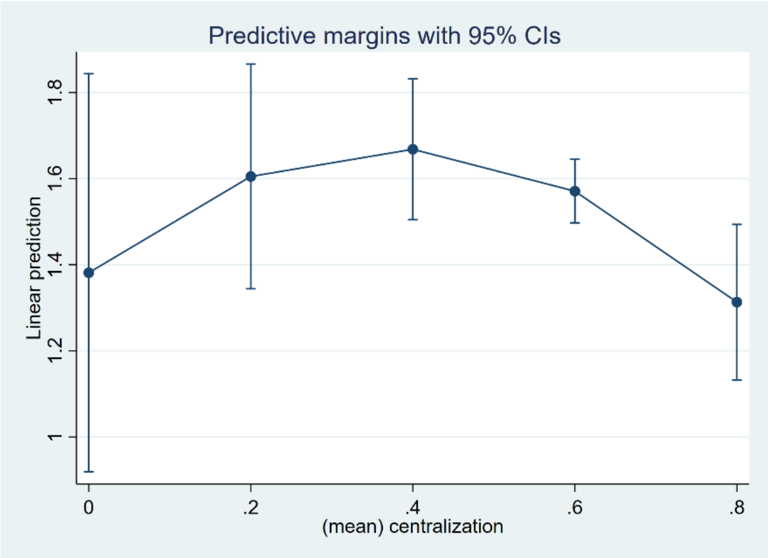


Figure E7. Relationship between community centralization and longevity, threshold 20%.
X axis: community centralization; Y axis: average community duration.

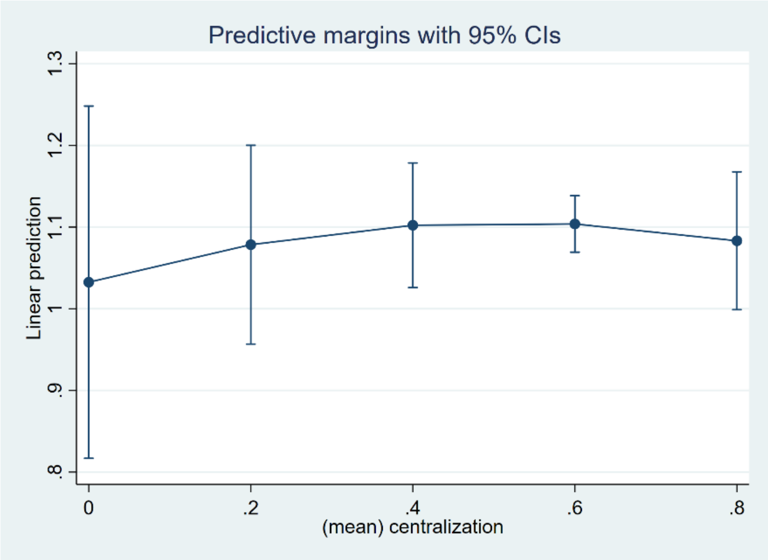


Figure E8. Relationship between community centralization and longevity, threshold 30%.
X axis: community centralization; Y axis: average community duration.

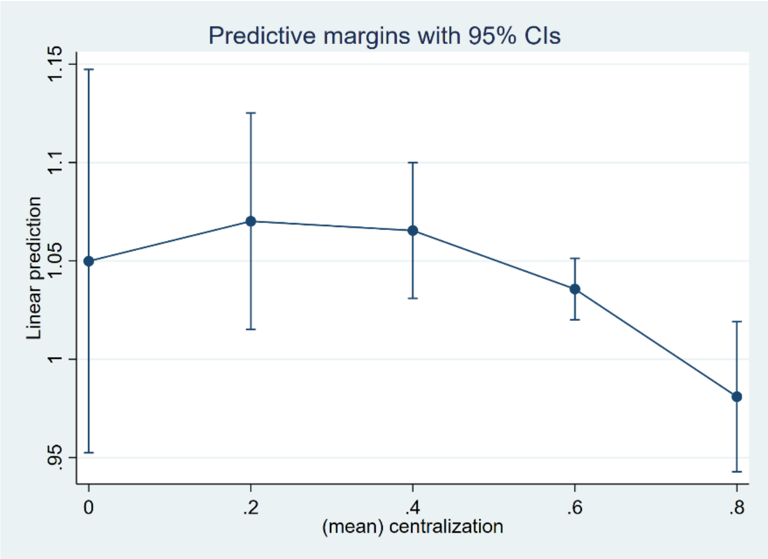


Figure E9. Relationship between community centralization and longevity, threshold 40%.
X axis: community centralization; Y axis: average community duration.

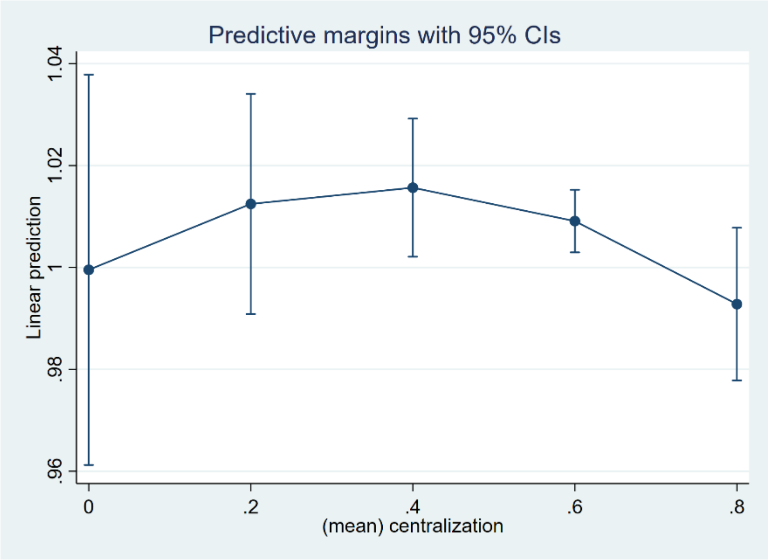
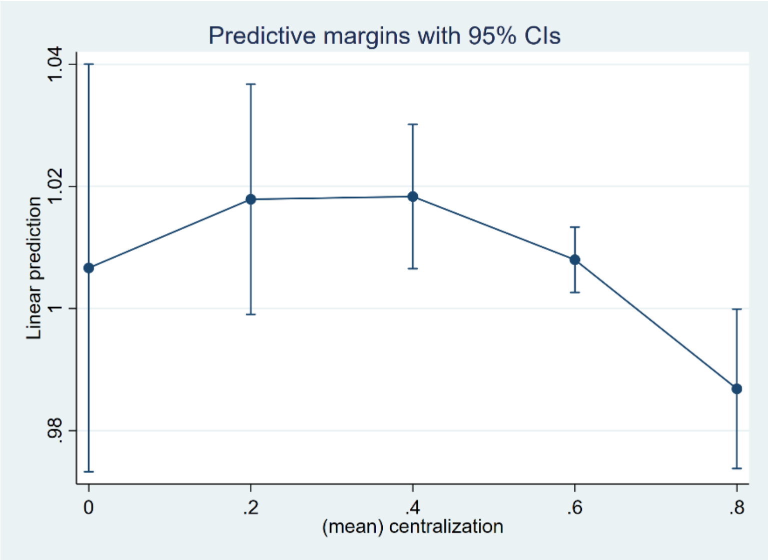


Figure E10. Relationship between community centralization and longevity, threshold 50%.
X axis: community centralization; Y axis: average community duration.



Chapter V: Conclusion

This dissertation was motivated by a desire to understand how groups of actors engaging in misconduct survive for longer or shorter periods of time. In glancing at any day's worth of headlines, it is obvious that organized misconduct is a widespread occurrence, and also that some groups are much better than others at perpetuating their misconduct while navigating institutional environments hostile to their efforts in varying degrees. Such behavior leads to significant costs for firms and society at large. Those costs are financial, reputational, and societal; they include significant physical and emotional harm, and even death (Greve, Palmer, et al., 2010; Palmer et al., 2016a). Organized misconduct is a foundational problem for firms and for society. And it seems like much of the time, it can perpetuate unabated for quite a while. What I wanted to know was: why? What differentiates these groups?

I situate my research in line with a few fundamental sociological and organizational inquiries. The first relates to misconduct as a key element of organizational and social life. Much research has explored antecedents and consequences of misconduct. It has explored misconduct through an individual lens (Ashkanasy, Windsor, & Treviño, 2006) and through the lens of organizational culture (Treviño & Youngblood, 1990). It has explored misconduct executed in the perpetrator's own self-interest such as with Bernie Madoff (Gibson, 2014), as well as executed on behalf of the organization, such as with Enron (McLean & Elkind, 2013). All of this is incredibly important work. What remains a large gap in our understanding, however, is the consideration of misconduct as a relational phenomenon that evolves over time.

Scholars have recently called for more research problematizing misconduct as a coordinated effort among multiple actors (Palmer & Moore, 2016; Brass et al., 2004). The reality is that many examples exist of pockets of coordinated actors engaging in misconduct while embedded within broader environments. Recent work has begun to explore misconduct as more of an organized and dynamic phenomenon (see Aven, 2015; Wang, Stuart, & Li, 2020; Zhang & King, 2021), but much remains unknown. This dissertation is a response to calls to better capture the structural components of misconduct and how those components relate to its sustainment over time.

The issue of sustainment, or duration, is also a key sociological and organizational issue (Lawrence & Winn, 2001). Longevity has long been recognized as a fundamental goal for organizational forms (Barnard, 1938; Dertouzos et al., 1989; Suarez & Utterback, 1995). My work reflects an institutional approach to this issue and specifically explores how norms and behaviors become legitimized over time and endure (Fligstein, 1991; Leblebici et al., 1991; Meyer & Rowan, 1977). Given the high risk of significant harm, I argue this is a particularly poignant question in the context of misconduct.

In undertaking the question of organized misconduct's longevity, I develop a novel community-based theory of misconduct and explore the structural attributes that contribute to the persistence of misconduct over time. I build from existing work that explores communities as distinct institutional orders that exert normative pressures and influence behavior of community members (Marquis et al., 2007; Marquis, Lounsbury, & Greenwood, 2011) . These localized pockets – though initially conceived of geographically but equally applicable to social or symbolic areas – establish their own sets of rules and expectations that govern behavior. This is true even if those localized norms are at odds with those of the broader institutional environment within which they are embedded (Davis & Greve, 1997). My research asserts that misconduct communities – that is, communities defined by misconduct relationships among actors – exert their own normative pressures and monitoring capabilities to enforce conformity among members. I use recent methodological advancements to empirically capture these communities as network communities – locally-dense social structures that are sparsely (or entirely non-) connected to other sub-groups within a larger network (Girvan & Newman, 2002; Newman & Girvan, 2004).

Using a network community level of analysis allows me to explore misconduct as a relational phenomenon that unfolds and evolves over time. Network communities remain under-theorized in organizational research despite demonstrating significant potential in shaping key network and organization outcomes (Gulati & Gargiulo, 1999; Sytch & Tatarynowicz, 2014). Recently, their potential is being exploited in the field of criminology, as interest grows to understand misconduct as a group-based endeavor (Bahulkar et al., 2018; Sangkaran, Abdullah, & JhanJhi, 2018). I use a community detection algorithm that has been demonstrated to accurately capture known instances of such misconduct – the Louvain algorithm (Jain et al., 2022) – and trace the longevity of communities over time in two different empirical settings: the Chicago Police Department (setting 1) and an online white supremacist chat forum I call Whitestorm (setting 2).

The reason I pursued two different empirical settings to answer my research question is that I wanted to be able to offer a more generalizable theory of organized misconduct that transcended any one particular context. Generally, attempting to study misconduct – especially over time – is very difficult due to data (un)availability and general lack of willing research partners (Wang et al., 2020; Zhang & King, 2021). I am fortunate to have found two creative ways to attain incredibly compelling research settings to help answer my research questions. The datasets themselves are a contribution to this line of research (Aven, 2015; Aven, Morse, & Iorio, 2019; Palmer & Yenkey, 2015), as they offer rich, longitudinal information that allows me to create network communities of actors and trace their survival over time. Combined, they help me shed light on the structural underpinnings of organized misconduct.

In my first empirical chapter, I use longitudinal data from 1991 – 2015 on the Chicago Police Department and construct a longitudinal dataset of complaints of severe misconduct filed against police officers. I use the Louvain community detection algorithm and locate 6,406 unique communities comprised of 8,983 police officers with 11,756 complaints of severe misconduct filed against them. In my second empirical chapter, I leverage data from a long-running white supremacist online chat forum and similarly use the Louvain community detection algorithm to locate 1,002 unique communities over 11 years of data (2002 – 2012) comprised of 15,956 white supremacists linked by 74,476 threads they post on in common. Across both studies, I operationalize social cohesion as community density (hypothesis 1) and the distribution of that cohesion (structural inequality) as community centralization (hypothesis 2).

The analyses from these studies suggest several propositions that help explain the persistence organized misconduct over time. First, social cohesion and structural inequality are two key structural characteristics that have been demonstrated to exert contradictory influences on community longevity in a range of contexts, both misconduct-related (Everton and Cunningham 2015, Wise 2014) and otherwise (i.e., Greve et al. 2010, Rowley et al. 2005, Sytch and Tatarynowicz 2014). This dissertation helps clarify these relationships by offering a unifying theoretical framework and testing my hypotheses in two unique, longitudinal datasets. I argue that these communities balance goals specific to wrongdoing: they attempt to conduct their activities while maximizing internal conformity and coordination and minimizing risk of detection or interference from outsiders (Baker & Faulkner, 1993; Bertrand & Lumineau, 2016; Morselli et al., 2007). My findings in both settings support both hypotheses – at all membership thresholds (10 – 50%) in the CPD, and at thresholds 20 – 50% in Whitestorm – and suggest a "sweet spot" of community structure that best enables these communities to survive over time. Thus, I propose:

> *Proposition 1: Community social cohesion and structural inequality both exert curvilinear effects on misconduct community longevity, such that as they each increase, they are initially assets for communities and increase community longevity; however, after a certain point, each of them become a liability and decrease community longevity.*

Next, in finding a longitudinal, statistically significant network community structure in both studies, these results suggest that, indeed, misconduct can be a relational phenomenon and that the characteristics of relationship structures matter for the longevity of those structures. While I am not able to test the underlying mechanisms put forth behind my hypotheses, my results are consistent with the idea that these communities operate as their own normative environments and that they are able to govern, direct, and constrain the behaviors of those within the community. Specifically, the results indicate that different structural characteristics are indeed helpful and then harmful for communities as they attempt to walk the line between operating efficiently but maintaining a protective buffer from would-be disruptors. That the results were robust across 10 different membership threshold specifications in two seemingly different settings reinforces the significance of the findings. Therefore, I propose:

> *Proposition 2: Misconduct groups fit within the theoretical concept of a community — that is, they do indeed encapsulate normative environments that govern, direct, and constrain the behaviors of community members.*

It does seem in some ways that each setting is quite different from each other. In Chapter Three, I explore communities of police officers linked by complaints of severe misconduct filed against them. Policing is inherently a group-based endeavor and the behavior in question is largely a reflection of interactions between police officers and civilians. This is behavior undertaken as part of a professional job. In Chapter Four, the communities I identify are among white supremacists posting together on the same threads in on online chat forum. These behaviors are anonymous and are decidedly *not* occurring in the "real world" offline, though research indicates that the ongoing exposure to such a chat forum increases the risk of significant harm and violence offline. Nonetheless, at first glance it seems that these settings encompass very different types of relationships made of very different behaviors.

And yet, the empirical results from both studies are remarkably constant. Using two such settings allowed me to parse misconduct situated in different organizational contexts and offer a more well-rounded theory that transcends context and reflects, perhaps, strategic cases reflective of different ends along a spectrum of organizational legitimacy. Along such a spectrum, one end includes licit organizations with mainstream societal aims and goals (North, 1991; Scott, 1995; DiMaggio & Powell, 1983), while the other end includes illicit organizations characterized by illegal activities, violence, or other forms of wrongdoing (Everton, 2012). The CPD arguably reflects the former – it is a fundamental social institution that is, generally, sanctioned as important and pursuant of legitimate and functional aims in society (Hunter, 1974). Whitestorm, in contrast, embodies more of the latter: it reflects an organizational form whose purpose is wrapped up in engaging in and perpetuating misconduct (Bouchard & Amirault, 2013; Shapiro, 2013). Based on these results, I propose:

> *Proposition 3: Misconduct communities specifically balance trade-offs related to maintaining community cohesion (loyalty, monitoring, and strong understandings of*

> *normative expectations) with avoiding attention and interest of hostile social control agents. They also navigate tensions between efficient chain-of-command structures with maintaining enough normative constraint evenly applied to all members, to prevent membership attrition. The core structural components of communities initially help, but then hurt, a misconduct community's ability to walk these fine lines.*

As discussed in Chapter Four, the findings are not significant at the 10% membership threshold in the Whitestorm setting. In that chapter I noted that specifically in an online context, it may be necessary to have higher levels of membership continuity over time in order to establish a stronger sense of normative pressures. Beyond that, establishing membership thresholds in the first place was a challenging endeavor as there was no real theoretical basis for doing so in the context of misconduct. I based my thresholds from extant work that explores longevity in very different contexts – the global computer industry (Sytch & Tatarynowicz, 2014), the Canadian investment bank industry (Rowley et al., 2005), and in the context of entrepreneurship enterprises (Vedres & Stark, 2010). Overall, my findings suggest that a specific membership threshold may not be as important as having one at all. That is, having some kind of measure for continued membership appears important, but the specification of that membership continuity may not be particularly significant. However, future work would benefit from more empirical exploration across varying shared membership levels and in additional organizational settings. Additionally, I measured community continuity at the yearly level, which seemed appropriate given the cadence of misconduct behaviors in both settings. However, other work has established continuity based on wider time windows (i.e., four-year windows; see Rowley et al., 2005). Thus, determining the appropriate time windows for misconduct community continuity may depend on the empirical setting. Future work would benefit from more exploration across wider and narrower time windows. To reflect this, I suggest that more specified shared membership thresholds would help improve our understanding of misconduct's duration, especially based on the organizational context within which misconduct communities are embedded.

In conclusion, this dissertation offers evidence that misconduct can indeed be considered a relational phenomenon shaped by the local social context within which it operates. My findings suggest that misconduct relational structures reflect coordination patterns between bad apple and bad barrel levels of analysis. Exploring the structural attributes of organized misconduct brings us closer to understanding: “how do they get away with it for so long?” This dissertation thus contributes to existing research by offering – and testing – a novel theory of the persistence of organized misconduct over time.

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