ABSTRACT OF THE DISSERTATION

Police officer networks and use of force behaviors

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The legal authority of law enforcement to use force is a defining part of policing, but one that comes with exceptional scrutiny and oversight. Discussions about policy reform and research on the determinants of police force are typically divided into three domains: situational contexts, organizational structure, and officer-level determinants. Noticeably absent from this area of research is the salience of networks in which officers engage and work in. These relationships are particularly meaningful given that police agencies do not teach misuses of power; rather, policing is known for its tight-knit culture, wherein officers are socialized through their interactions with one another.

The current study extends this line of inquiry. It uses administrative data obtained from the Force Report (i.e., formal use of force reports) to investigate the role of officer networks in facilitating use of force behaviors. First, it investigates the interplay between officer attributes and the social structure of force networks to predict co-involvement between officers in a use of force incident. Second, it employs a group-level approach to evaluate whether officers in a shared working environment engage in similar use of force patterns. Finally, it adopts a predictive approach to identify focal officers with high-risk profiles relative to their colleagues.
Findings indicate that, much like other forms of crime and deviant behaviors, police use of force is influenced by individual, dyadic, contextual, and network processes. While the grouped nature of force is confirmed in Study 1, with the use of force found to be concentrated on a subset of officers, there exists variation in officers' likelihood of using force together. Indeed, force is more likely to occur between officers similar in race and experience than those dissimilar. Despite an emphasis on the collective nature of force, with departments likely to specialize in the use of physical force, Study 2 finds that key organizational and environmental determinants are associated with versatility in types, and thus, degrees of force employed. Lastly, provided that a small proportion of officers are responsible for a disproportionate proportion of incidents, in Study 3, five groups (i.e., bad barrels) and 11% of officers (i.e., bad apples) in the largest connected component are identified as exhibiting high-risk behaviors. Relative to similarly situated peers, these officers use force more frequently and demonstrate the widest social reach, making them an efficient starting point for intervention and prevention purposes.

By focusing on relational patterns at the partnership, group, and department level, the current study builds on the interdependent nature of the police role to understand when and why force happens. Specifically, it demonstrates how police data can be leveraged to potentially mitigate behaviors that may lead to greater instances of police violence while outlining strategies that may improve police-community relations.
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It is not a coincidence that much of my work is based on network theory. What matters to me are relationships - the interdependencies between individuals, the collective ways we work together, and the outcomes of these relationships. This dissertation is one example.

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To my constants - you continuously teach me the importance of kindness. I am grateful for your support, patience, and unconditional love.

Love and respect, always

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INTRODUCTION

The legal authority of law enforcement to use force is a defining part of policing, but one that comes with exceptional scrutiny and oversight (Bittner, 1970). A string of high-profile incidents between civilians and the police in or around Chicago (Fan, 2018), Indianapolis (McQuaid, 2016), New York City (Minchillo, 2014), Los Angeles (Winton, Parvin & Morin, 2018), Baton Rouge (CBS News, 2016), Philadelphia (Wood, 2013), Falcon Heights (CNBC, 2016) and Ferguson (Osunsami and Knox, 2017) has renewed a much-needed discussion on the prevalence of use of force. Police are tasked with enforcing laws, preventing crime, and maintaining public order. Officers must respond to emergency and non-emergency calls, monitor criminal activities, and engage with the public in unfamiliar contexts where they must be prepared to use force to ensure public safety (Alpert & Smith, 1994; McDonald et al., 2003; Reiss, 1970; Terrill, 2005).

Whether force is measured through use of force reports, civilian complaints, victim surveys, or observational methods (Adams et al., 1999; Adams, 1996; Jefferis et al., 2011; Prenzler et al., 2013), it is widely acknowledged that police use of force is relatively rare, but can have consequential effects. For example, the Bureau of Justice Statistics Police-Public Contact Survey (PPCS) reported that in 2015, 21% of the U.S. population aged 16 or older had experienced some type of contact with the police in the last 12 months (Davis, Whyde & Langton, 2018). Among the 53.5 million residents who reported contact, roughly 2% of all police-civilian encounters resulted in the use of force or the threat of force. The vast majority (83%) of those subjected to force or the threat of force perceived the officers’ actions to be excessive, with 89.5% of residents reporting that the police acted improperly.
Force, however, becomes particularly problematic when it becomes a normalized means of conflict management, such that officers learn to resort to it quickly, frequently, and demonstrate select and repeated patterns of using force. These interactions have an overarching effect on the public’s views and responses to the police (Desmond et al., 2016; Lasley, 1994; Lersch & Mieczkowski, 2005; Weitzer, 2002). Civilians perceptions of officers employing unnecessary or excessive levels of force can decrease police legitimacy (Brunson, 2007; Gau & Brunson, 2010; Tankebe, 2009; Westley, 1970) and potentially lead to tragedies such as the loss of civilian and officer lives (Batchelor, 2016; Edwards et al., 2018; Sierra-Arévalo, 2019), civil disorder (Pyrooz et al., 2016; Shjarback et al., 2017; Wolfe & Nix, 2016), criminal prosecution (Ross, 2019) and civil proceedings (Newman, 2019; Emery & Maazel, 2000; Kish-Gephart et al., 2010; Skolnick & Fyfe, 1993).

Discussions about policy reform and police use of force are typically divided into three domains. The situational context framework draws on the role of social status and neighborhood context. This perspective posits that policing styles are influenced by communities' demographic composition and structural characteristics (Shjarback, 2018; Sobol et al., 2013; Terrill & Reisig, 2003). The organizational structure framework draws on the organization's formal and informal features or agency (Alpert & MacDonald, 2001; Friedrich, 1980; Shjarback & White, 2016). This perspective prioritizes characteristics such as departmental size, rules, regulations, bureaucracy, and professionalization as the main drivers of police abuses (Crank et al., 2007; Herbert, 1998; Kappeler et al., 1998; Klockars, 1980). Finally, officer-level determinants draw on officer attributes to explain police behaviors. This perspective focuses on the personality traits or characteristics of individual officers, including their race/ethnicity, sex, education, temperament, and
psychological dispositions to explain excessive or unnecessary uses of force (Brandl et al., 2001; Brandl & Stroshine, 2013; Chappell & Piquero, 2004; Kish-Gephart et al., 2010). Noticeably absent from this area of research is the salience of social networks in which officers interact, engage, and work in. The importance of officer peer groups is rooted in decades of ethnographic research (Muir, 1979; Niederhoffer, 1967; Skolnick, 2011; Westley, 1953, 1970); however, with a few notable exceptions (Ouellet et al., 2019; Quispe-Torreblanca & Stewart, 2019; Wood et al., 2019; Zhao & Papachristos, 2020), scholars have largely overlooked the role of peers in enabling exposure to, and the propensity to spread, and escalate use of force behaviors. Interactions with peers and colleagues are particularly relevant given that police agencies do not teach such abuses of power; rather, policing is known for its tight-knit organizational culture where officers learn and conform to different forms of conduct through their interactions with one another.

**Research Inquiry**

The dissertation aims to extend this line of research by examining the role of officer networks in facilitating use of force behaviors. Data from the *Force Report*, a database consisting of every force report filed in a local police department in New Jersey, the United States, from 2012 to 2016, are used to drive three studies. The first study is mainly descriptive and applies a network approach to understanding police partnerships by examining the probability of a tie forming between officers. Namely, it considers whether (and which) officer-level attributes are associated with the likelihood that officers will select to use force together. The second study employs a group-level approach, determining the nature and type of force within and between officers in a shared working environment (i.e., same department). It examines the extent to which departments specialize or show
versatility in their use of force practices. These two studies adopt a social learning perspective that suggests that individuals acquire the definitions, skills, beliefs, and rationalizations that facilitate crime and deviance through their interactions with others.

Finally, the third study applies a predictive approach. It evaluates officers’ structural position to identify focal officers embedded in densely knit “local groups” within the broader network. These officers, relative to other officers in the network, have high-risk profiles. They demonstrate elevated levels of using force with their centrality and connectivity in the network enabling them to reach other officers more efficiently than their colleagues. Though each study draws from an occupational subculture perspective, it integrates a criminological framework to add to our understanding of how officer networks shape and determine the nature, pattern, and degree of police use of force. Specifically, police use of force aligns with this paradigm with seasoned officers and select colleagues serving as conduits of information, support, guidance, and teachers of crime and deviant behaviors.

**THEORETICAL AND CONCEPTUAL BACKGROUND**

**Beyond defining and measuring police use of force**

The extent to which the police use, and potentially misuse, their authority to inflict force is an ongoing discussion among the public, practitioners, policymakers, and law enforcement officials. Though agencies have standard operating procedures for applying force and set guidelines to direct officers on what constitutes appropriate use of force versus excessive use of force, there is considerable variation in policy and practices across agencies. Similarly, while the literature on police use of force is widespread, it varies on what
constitutes “force” and how use of force is (or should be) measured (Garner et al., 2002; Hickman et al., 2008; Terrill & Mastrofski, 2002).

To start, scholars have failed to “conceptualize fully and to measure consistently police use of force” (Engel, 2008, p. 557) with evaluations and estimates varying across departments, agencies, and methodological approaches. Various sources of data have been used to measure force. For example, Bayley and Garofalo (1989), Fyfe (1989), and Worden (1995) use systematic field observations of violent or potentially violent interactions between civilians and police officers. Friedrich (1980) followed Reiss’s (1970) methodology, relying on observers to determine whether force had been used. Kavanagh (1997) and Lundstrom and Mullan (1987) measured force directly, turning to custody arrests and instances of resisting arrest in police-civilian encounters. Croft (1985) and Meyer (1992) turned to “use of force” reports completed by officers, whereas Chevigny (1969), Pate and Fridell (1993), Russell (1978), Hickman (2006) measured force indirectly, using civilian complaints about police use of force. Together, Hickman, Piquero, and Garner (2008) reviewed 36 publications on police use of force. Their review found that scholars used six different sources of data (i.e., arrest reports, household surveys, independent observations, police surveys, suspect surveys, and use of force forms) to measure police uses of force with the “highest estimate of force reported to be 30 times greater than the lowest estimate” and reported that rates conditioned on “measures of force used, the types of incidents studied, and the jurisdictions included” (p. 572).

Police use of force has been measured dichotomously, classified into “justified use of force” versus “excessive use of force” (Alpert & Smith, 1994; Garner et al., 1995; Smith, 2008;) treated as a dynamic process that is conceptualized on a continuum that ranges from
minor (e.g., verbal commands, gestures, warnings, and unholstering a weapon) to deadly (e.g., firearms, lethal consequences) (Crawford & Burns, 1998; Garner et al., 1995; Klinger, 1995; Smith, 2008), and categorized into multiple categories of force (e.g., Garner et al., 2002; Terrill & Mastrofski, 2002). While scholars have applied various measures of force, policies on the use of force, and police training manuals commonly refer to a "continuum of force" (Americans for Effective Law Enforcement, 1988; Clede & Parsons, 1987; Connor, 1991; Desmedt, 1984; Garner et al., 1995) that captures the gradations in the severity of force incidents to minimize officer discretion and provide systematic guidance by specifying the appropriate response for a given level of suspect resistance (Alpert & Dunham, 1999; Garner et al., 1995; Klinger, 1995; McElvain & Kposowa, 2008; Terrill & Mastrofski, 2002). Policies linked to a force continuum rank various types (and levels) of force on an ordinal scale. Officers are directed to respond with a level of force appropriate to the severity of the situation and the degree of resistance posed by the subject (McEwen, 1997). The general assumption is guided by the fact that officers may gradually move (escalating or de-escalating force) from one part of the continuum to another, if necessary (Terrill, 2001). Indeed, several continuums of force have been proposed ranging from the linear design (McEwen, 1997), modified linear design (Connor, 1991), matrix form or force depicted by a wheel (Hoffman et al., 2004). These continuums match the degree of subject resistance in relation to the appropriate uses of police force available.

Even with the added transparency and guidance provided by the use of force continuum, there is little uniformity on what types of force fall within the continuum across agencies. This led Terrill, Paoline, and Ingram (2012) to conclude that agencies have no standard practice. In their report to the Department of Justice, where they compared eight
agencies across a multitude of factors, they found that while many police agencies still use a force continuum approach, specifically a linear continuum, there is no “commonly used means of tactical placement in terms of force continuum policies as types of force are not uniformly categorized in police agencies force continuums” (p.iii). In part, they attribute this to agencies having their own organizational culture, which shapes what is considered sufficient force and excessive force during police-civilian encounters. Some agencies exercise relatively restrictive policies, whereas other agencies exercise relatively liberal policies that place greater discretion in officers’ hands. While there are no definitive ways to refine definitions (e.g., what is force, what is not force, when is force excessive) and measurement issues regarding use of force practices, the capacity to use force are more likely during specific types of encounters (i.e., arrests see Hickman et al., 2008) with the causes and correlates of use of force decisions vital in understanding the underlying contextual factors that drive practices, and thus, offer more systematic explanations of force used.

**Explanations of police use of force**

The policing profession facilitates opportunities for crime and delinquent behaviors that far transcends other occupations (Barker, 1977; Bittner, 1970; Reiss, 1970). Law enforcement officers have the authority to use force during their normal working hours, and at times, rely on force or the threat of force to enforce the law and protect the public (Bittner, 1970). To date, a host of determinants related to policing and use of force have been studied, such as:
1) *excessive use of force* (Alpert et al., 2004; Alpert & Smith, 1994; Atherley & Hickman, 2014; Brandl et al., 2001; Roithmayr, 2016; Skolnick & Fyfe, 1993; Smith & Holmes, 2014; Wolfe & Piquero, 2011);

2) *deadly force* (Bor et al., 2018; Edwards et al., 2018, 2019; Fyfe, 1988; Geller, 1982; Jacobs, 1998; Klinger et al., 2016; McElvain & Kposowa, 2008, 2008; White, 2001);

3) *situational/environmental factors* (Brunson & Weitzer, 2009; Eitle et al., 2014; Kane, 2002; Lee et al., 2014; Lee, 2016; Shjarback, 2018; Smith & Holmes, 2014; Sobol et al., 2013; Sun et al., 2008; Terrill & Mastrofski, 2002; Terrill & Reisig, 2003);

4) *organizational factors* (Alpert et al., 2012; Alpert & MacDonald, 2001; Cao, 1999; Cao et al., 2000; Eitle et al., 2014; Hickman & Piquero, 2009; White, 2001; Wolfe & Piquero, 2011); and

5) *problem officers* (Brandl et al., 2001; Brandl & Stroshine, 2013; Chappell & Piquero, 2004; Donner et al., 2016; Fyfe, 1988; Harris, 2010; Kish-Gephart et al., 2010; Lersch & Mieczkowski, 1996; McElvain & Kposowa, 2008; Terrill, 2005; Terrill & McCluskey, 2002; Toch, 1996)

These studies can be classified into 1) situational-level, 2) organizational-level, and 3) officer-level determinates.

**Situational context and police behaviors**

Centering on the sociological (situational) domain, scholars have examined police-civilian interactions' situational characteristics (Chevigny, 1969; Kane, 2002; Klinger, 1997; Terrill & Reisig, 2003; Worden, 1995). These studies collectively argue that the local
community or neighborhood where police organizations serve shapes and influences police behaviors (Bass, 2001; Smith, 1984). For example, Black (1976) suggested that the manner and application of punishment applied by agents of the state is dependent on aspects of social space where subjects are located. Black (1976) posited that police would be more punitive (e.g., forceful) toward suspects located in poor neighborhoods, focusing primarily on minorities and the young. These individuals are perceived by the police as more deserving of control and punishment (Bayley & Mendelsohn, 1968) with Takagi (1981), stating that “police have one trigger finger for Whites and another for Blacks” (p. 30).

Terrill and Reisig (2003) use observations, census data, police crime records, and in-person interviews with police officers collected by the Project on Policing Neighborhoods (POPN) in twelve beats in Indiana and Florida. They found that net of suspect behavior, characteristics, and a host of other relevant controls, higher levels of force were significantly more likely to be used against suspects in high crime (i.e., high homicide rates) and disadvantaged neighborhoods. They also found an association between the suspect’s sociodemographic characteristics and level of force, such that net of encounter-level statistical controls, male, minority, young, and lower-income suspects were more likely to be on the receiving end of higher levels of police force. They situate their findings with the context of Reiss and Bordua’s (1967) discussion, arguing that police officers place civilians into a dichotomy: those that deserve to be punished and those that do not, touching on broader systematic issues. In this context, racial and ethnic minorities and lower-class members are more likely to be subjected to police force (Nix et al., 2017; Worrall et al., 2018).
In support of these findings, Sun et al. (2008) examined the influence of officer and neighborhood characteristics on the relationship between situational factors and officers' coercive and non-coercive behaviors. Mainly, officers were more likely to conduct coercive action in socially disadvantaged neighborhoods, with males, minorities, and civilians from a lower socio-economic background more likely to be subjected to coercive activities than their counterparts. Apart from community police officers, who were significantly less likely to engage in non-coercive activities than other officers, no other situational characteristics played a vital role in determining officers’ non-coercive actions.

Similarly, using observational data obtained from sixty neighborhoods, served by twenty-four police departments in New York, Missouri, and Florida, Smith (1986) employed an empirical test, examining the relationship between police behavior and neighborhood characteristics. Smith (1986) defined police behavior as investigative police-initiated contacts, proactive assistance police-initiated contacts, arrests, coercive authority whereby the suspect was unarmed, and the police use or threat to use force. Smith’s (1986) findings revealed that, net of all else, neighborhoods' socioeconomic status was a determinate for arrests. The racial composition of neighborhoods determined the likelihood that the police would exercise coercive authority. In other words, police were more likely to use coercive authority in primarily Black and racially heterogeneous neighborhoods, with arrests less likely to occur in high-status neighborhoods relative to low-status neighborhoods.

Other studies have not necessarily uncovered a consistent “neighborhood effect” on police use of force. Instead, scholars have either provided an alternative hypothesis for elevated use of police force, empirical evidence of a null relationship, or variations across
force and crime types. For example, in Smith’s (1986) study above findings were conditioned on the suspects’ race. Police were less likely to use coercive authority on Black suspects in White neighborhoods and were more likely to use coercive authority on Black suspects in Black neighborhoods. As such, Smith (1986) concluded that “coercive authority is not influenced by the race of the individual suspect” (p. 332) instead, “the racial composition of neighborhoods has a significant effect on the propensity of police to exercise coercive authority toward the suspect” (p. 336). Likewise, Lee (2016) used a random sample of NYPD Stop, Question and Frisk data, census data, and crime data to examine the effects of situational and community factors on police use of nonlethal force compared to no force. Findings revealed that in cities with a higher percentage of White residents, officers were less likely to use non-lethal force. However, a White suspect was more likely to encounter police use of force in a community with higher violent crime rates. More notably, the percentage of Black or Hispanic suspects within the community district was not associated with the likelihood of police using force on Black and Hispanic suspects.

Turning to more severe uses of force, Lawton (2007) used multilevel models to examine whether levels of self-reported police use of nonlethal force varied across locales in Philadelphia, Pennsylvania. They found that neither officer race, civilian race, or officer-civilian race combination played a significant role in police use of force. Rather officer force history and civilian behaviors and demeanor were associated with a higher level of force being applied. They suggest that it might be the case that race plays a more substantial role in incidents where lower degrees of force are used as opposed to experiences where more severe force is used. To this end, Klinger et al. (2016) examined police use of deadly
force using data on 230 police shootings in St. Louis, MO, between 2003 and 2012. As expected, they found that officer-involved shootings were prevalent in a relatively small number of socioeconomically disadvantaged neighborhoods with a relatively sizeable Black population and higher levels of firearm violence. However, the association between firearm violence and the frequency of officer-related shootings was curvilinear, with multiple officer-involved shootings occurring less frequently in these neighborhoods. They concluded that neighborhood racial composition and socioeconomic status did not significantly impact the frequency of officer-involved shooting. Instead, police use of deadly force resulted from serious crime in neighborhoods – with elevated firearm violence levels driving officer-involved shootings. Relatedly, Ross (2015) aimed to evaluate county-level racial bias in police shootings. Ross (2015) found considerable heterogeneity across counties in the extent of racial bias in police shootings. His study, however, provided no empirical support that racial bias in police shootings was driven by crime rates or even race-specific crime rates (assault-related or weapons-related).

When it comes to understanding the association between situational contexts and police use of force, findings are not linear nor consistent across time, place, or social contexts. This is because studies have elected to use various methodological approaches and ask somewhat different research questions. These discrepancies lead to variations in the generalizability and salience of such findings. Knowledge concerning the association between race, crime, socioeconomic status, and police use of force remains limited, with a need to consider factors at the organizational/agency level and officer level.
Structural features of the organization

The prevalence of force is also generated through organizations' and police agencies' characteristics (see Friedrich, 1980; Worden, 1995). For example, Smith (1984) posits that "any theory of legal control that ignores the organizational context in which police operate cannot adequately account for police behavior across different organizational contexts" (p. 33). Departments act as formal organizations with a host of rules, norms, and hierarchal structure that controls and further regulates its members' activities (Mastrofski, 2004, p. 103). The department and the organization's informal system influence police discretionary decision-making, creating variation in police behaviors and paving the manner and method for police use of force.

Several seminal studies of police have stressed the importance of informal organizational culture as a determinant of police behavior (Klinger, 1997; Skolnick, 1966, 2011; Skolnick & Fyfe, 1993; Wilson, 1968). Wilson (1968) provided a typology of police agencies centered on organizational theory related to police behavior. Wilson (1968) examined officers' behavioral patterns in eight police departments, arguing that administrators, who themselves are constrained by the community's political climate and cultural landscape, shape behavior, and police culture patterns. In particular, Wilson (1968) found that American police have three primary functions: law enforcement, order maintenance, and provision, specifying three complementary operational styles of policing (i.e., legalistic, watchman, and service), to determine how local political culture impacted organizational priorities among police organizations (also Zhao & Hassell, 2005).

According to Wilson (1968), departments that follow a legalistic style of policing are “by the books.” Legalistic style of policing stresses high-performance rates and an
emphasis on enforcement. Officers are tasked with making arrests, providing greater traffic enforcement (e.g., issuing tickets), and policing the illicit market. The central and single goal of these agencies is to enforce the law. Smith (1984) found that officers in legalistic departments were two to three times more likely to arrest juveniles than officers in watchman or service agencies. These departments adopt a hierarchical structure that sees decisions being made from the top down with little to no input from subordinates or civilians. Because officer discretion is perceived to be unethical – generating an opportunity for corruption – officers are trained to treat all civilians equally and to operate autonomously from the community, relying heavily on the rules and procedures of central administrative authority and “rationality in achieving its goals” (Zhao & Hassell, 2005, p. 412).

*Watchman-style* policing operates in communities that generate more calls for services. The Watchman style of policing stresses order-maintenance. Structurally, these departments have flat bureaucratic structures. These departments employ and provide discretion for officers. Officers are likely to overlook minor infractions, less severe crimes and focus on infractions that disrupt the community's peace and order (Wilson, 1968, p. 140). Namely, laws that are important to civilians and local politicians (Wilson, 1968, p. 141). Given this emphasis on discretion, officers are often subject to corruption and allegations of excessive force. This is reflected in officer profiles: mostly working-class, recruited locally, low paid, and poorly trained with minimal to no advancement opportunities. Likewise, because these departments operate on low budgets and are likely to be established in lower-income communities, they have limited specialized tasks and roles and few guidelines to systematically enforce the law.
Finally, *service style* policing operates in departments that emphasize community demands, problem-solving and maintaining public relations. Service agencies are decentralized, such that they have many stations or precincts presiding over individual beats. These departments have less of a hierarchical structure but tend to be specialized and professional. Like the watchman style, officers avoid making arrests by ignoring minor infractions; however, they tend to place greater weight on crimes that impact civilians' welfare, such as robberies and burglaries (Wilson, 1968, p. 201). These departments are located in smaller, middle to upper-class homogenous areas with little violence. Because civilians in these areas tend to be affluent, agencies have the financial and technological means to retain highly experienced and well-educated officers to preserve safety and public order.

Since Wilson’s study in the 1960s, much has changed in how police do their jobs and police agencies' organizational behavior across the country. More recently, studies have focused on how core features of the department/ and or agency such as structure, reporting behaviors, use of data, professionalism (e.g., commitments, specialization, community policing), administrative policies and training, and size shape police-civilian encounters (Alpert & MacDonald, 2001; Brown, 1981; Eitle et al., 2014; Fyfe, 1979; Klinger, 2009; Mastrofski, 1981; Riksheim & Chermak, 1993; Shjarback & White, 2016; Terrill & Paoline, 2017). For example, Alpert and MacDonald (2001) examined the relationship between agency structure and force rates. They used departmental use of force data from a national probability sample of law enforcement agencies by the International City Managers Association. Alpert and MacDonald (2001) focused on five agency-relevant measures: Commission on Accreditation for Law Enforcement Agencies (nationally),
accreditation (state-level), union, use of data and data management, and if the individual or supervisor completed the use of force report form. They also controlled for the violent crime rate of the responding agency and agencies' region. They found substantial variation in handling force data across geographic differences with reports of force highest in the South (v. North, West, East) and agencies situated in areas with higher violent crime rates.

Focusing on agency-level determinates, they found that jurisdictions that use their data for a specified purpose (e.g., data for management and administration) reported higher incidents of force, whereas agencies that required officer accountability such as requiring supervisor or other department personnel (as was common in the West) to fill out the use of force reports had lower incidents of force. They found no evidence that a collective bargaining unit or union, or whether the agency was accredited or (nationally or at the state level), was associated with variation in force used. Ultimately, their findings point to the linkage between the violent crime rate, the department's organizational context, and incidents of force.

Terrill and Paoline (2017) employed a national multi-agency approach, examining 3,340 use of force incidents (via officer use of force reports) across three US agencies. They aimed to evaluate how administrative policies on force were related to variations in force levels. Because each of the three agencies varied in terms of policy direction, guidance, and restrictiveness, Terrill and Paoline (2017) could draw comparisons across the agencies while considering agency size and city characteristics. Controlling for various factors such as civilian resistance, race, sex/gender, age, drugs/alcohol, weapon possession, and mental impairment as determined in the use of force reports – they found that similar to use of deadly force, whereby restrictive lethal force policies were found to be associated
with fewer police shootings of civilians (also see Geller, 1982; Sherman, 1983; Uelmen, 1973), officers in agencies that relied on more restrictive policies used force less readily than in agencies with less restrictive policies. Notably, they found that officers at the largest agency (i.e., the largest number of sworn officers and civilian population) with the highest crime rates and more restrictive force policy directives employed less force in comparison to the other two agencies. Their results underscore the importance of administrative policy with respect to police use of force outcomes (also see White, 2001) with efforts calling on restricting officer discretion in applying lethal force.

Shjärback and White (2016) focused on the relationship between five departmental professionalism measures: agency commitment to education, hiring or screening, standards, the total number of training hours, female representation, and agency commitment to community policing and violence in police-civilian encounters. They use data from the 2003 Law Enforcement Management and Administrative Statistics survey to examine police-civilian violent encounters across 526 large municipal law enforcement agencies. Police-civilian violent encounters were captured through formal civilian complaints of officer use of force. Consistent with similar studies (see Goel & Nelson, 1998; Eitle et al., 2014; Cao et al., 1999, 2000), they found that department size and a jurisdiction’s crime rate were significantly, and positively, related to the department’s rate of force complaints; however, of their five measures of departmental professionalism, only departmental commitment to education was found to be significantly associated with rates of civilian complaints and officers assaulted on shift. Specifically, they found that in comparison to departments that only required a high school diploma, departments that required officers to have earned at least an associate degree before being hired experienced
lower rates of civilian complaints of use of force and reported few officer assaults on shift. They aligned their findings with Repetto (1974), noting the dynamic nature of the profession, whereby officers are expected to occupy several roles (i.e., social workers, counselors) during their shift. As such, it is beneficial that officers are formally educated and socialized to carry out these roles (see Kappeler et al., 1992; White, 2007).

Together, results demonstrate a link (though trivial) between use of force, defined through force reports or civilian complaints, and various organizational measures. However, findings are not without limitations. Studies examining departmental/organizational level predictors are challenging to conduct and vary on levels of measures given the "expense and difficulty of collecting comparable data on multiple agencies" (Worden, 1995, p. 35). Studies that have examined police use of force at the organizational level are not easily comparable as not every agency collects (or shares) use of force data. Namely, these studies succumb to sampling bias, spurious findings, and generalizability issues with discrepancies in how agencies regulate, measure, and record force incidents.

**Specified officer level determinates**

Conversely, a host of studies have relied on officer attributes to explain incidents of force. Studies that have adopted the officer-level approach contend that specific “types” of officers are conducive to a preferred policing style, increasing (or potentially decreasing) the likelihood of using force than other officers. Though studies report mixed or inconclusive findings between officer level demographics, experience, education, social and psychological factors, and police use of force, several themes emerge.
Race/ Ethnicity. Studies have found that in comparison to White officers, minority officers are more likely to use physical force (Garner et al., 2002), to be the subjects of complaints about excessive use of force and misconduct (Cohen & Chaiken, 1972; Kane & White, 2009; White & Kane, 2013) and to use force against suspects of their own race (Alpert & Dunham, 1999). For example, Sun and Payne (2004) examined the influence of officer race on police coercive and non-coercive actions finding that Black officers were more likely than White officers to respond coercively when resolving conflicts between civilians. In contrast, Garner et al. (2002) found that Hispanic officers use more physical force in comparison to White officers. However, they did not differ in terms of the severity of the force used. It has been argued that these findings are an artifact of job assignment (Alex, 1969; Kuykendall, 1980). Minority officers are more likely to be assigned to patrol or live in predominantly non-White neighborhoods with higher crime rates (Anderson, 1990). In these areas, police have greater exposure to interactions that may require using force, or they might elect to use traditional tactics (e.g., stops, searches) in the aims that these infractions might lead to larger busts or to boost arrest rates (Brunson & Weitzer, 2009; Moskos, 2008).

An alternate interpretation is to recognize the complexities that arise between one’s racial identity and occupational identity. Notably, for Black officers, the tension that arises from choosing to be “Black” versus “blue” in their relations with the community and with each other (see Alex, 1969; Bolton & Feagin, 2004; Leinen, 1985; Moskos, 2008; Sun & Payne, 2004; Weitzer, 2000). For example, Weitzer (2000) and others suggest that Black officers that embrace “the blue cop” mentality are likely to act more aggressively towards Black civilians to show their commitment and dedication to their police identity. (p. 322;
also see Alex 1969; Leinen 1985; Moskos 2008) and to earn the respect of, and maintain authority over, the communities that they police (Leinen, 1985).

Other studies, however, have found the opposite effect or no effect. For example, a host of research finds that Black officers are less like to receive fewer complaints and are implicated in fewer cases of serious misconduct that involve use of force and firearm incidents than White officers (Brandl et al., 2001; Fyfe, 1988; McElvain & Kposowa, 2008; Terrill, 2005; Terrill & Mccluskey, 2002; Wolfe & Piquero, 2011). Likewise, in comparison to their White counterparts, it has been found that Black officers engage in less abusive and more supportive actions in predominantly non-White neighborhoods (Sun & Payne, 2004). This has been attributed to a “shared cultural experience” where minority officers are presumed to understand better the needs of the communities they police. As such, Black and Hispanic officers may be better equipped to de-escalate police-civilian encounters and relieve tensions between civilians and the police (Decker & Smith, 1980; also see Kelly & Farber, 1974; Kelly & West, 1973; Leinen, 1985; Walker, 1983).

Studies have also found no relationship between race/ethnicity with the appropriateness or degree of police use of force (Crawford & Burns, 1998; Paoline & Terrill, 2007; Terrill 2001; Terrill & Mastrofski, 2002). Using data from the Philadelphia Police Department, Lawton (2007) examined self-reports of force over one year. He found that neither officer race, civilian race, or the officer civilian race combination played a significant role in the use of nonlethal force. Likewise, examining police use of force in Phoenix, Crawford and Burns (1998) found that officer race/ethnicity did not influence whether force was employed or the type of force use (i.e., verbal commands, physical
restraint, chemical spray, tactical non-lethal weapon, or firearm use) net of officer characteristics, suspect characteristics and the situational context (p. 46).

Sex. Turning to officer sex, studies overwhelmingly suggest that male officers are significantly more likely to use force (Garner et al., 2002; Locke, 1996; McElvain & Kposowa, 2008), use higher levels of force (Paoline & Terrill, 2005a), and be to be investigated by internal affairs than female officers (McElvain & Kposowa, 2004). Research on female police officers has purported their policing styles to be different from males. It has been argued that female officers are unwilling or incapable of displaying coercive activity and are less likely to demonstrate aggressive behaviors like make arrests, issue tickets, use deadly force, and be involved in deadly force situations (see Bloch & Anderson, 1974; Grant, 2000; Hale, 1992; Herbert, 2001; Lonsway, 2001; Paoline & Terrill, 2005a). Because female officers are less likely to demonstrate “aggressive” behaviors, they are less likely to receive civilian complaints and be involved in incidents that require force. For example, Greene et al.’s (2004) study of the Philadelphia Police Department found that female officers were 38% less likely to be involved in misconduct complaints than male officers.

Findings outlining significant variations between male and female patterns of use are not conclusive (see Crawford & Burns, 1998; Lawton, 2007; McCluskey & Terrill, 2005; Paoline & Terrill, 2005a; Terrill et al., 2008; Terrill & Mastrofski, 2002; Worden, 1996). Paoline and Terrill (2005a) explore various analytical techniques to compare the type and frequency of coercion that female and male officers use in their day-to-day encounters. They found that female police officers were not more reluctant to use coercive force than their male counterparts and “that male and female officers used coercion in
similar proportions, and both tended to use verbal force at higher rates when compared to physical” (p. 114). Though males were significantly likely to use higher levels of force against male suspects, females' levels of force were statistically independent of the suspect’s sex. These findings were supported by McCluskey and Terrill (2005), who found that officer sex was not related to use of force, net of the number and type of complaints filed against officers, and Terrill and Mastrofski (2002) who suggested that net of situational and suspect characteristics there were no significant differences in how male and female officers employed force.

*Experience and age.* Generally, it has been found that both age and experience are linked to police use of force. Indeed, it could be inferred that the higher the age, the greater the experience, as officers are likely to enter the profession when they are young and become more experienced over time. For example, Paoline and Terrill (2007) find that each year of experience gained by the officer diminishes the use of verbal or physical force.

Experience can be linked to hiring practices, deployment activities, and assignment strategies. More experienced officers are less active in patrol duties or placed in administrative or managerial roles that reduce their exposure to the public (Aamodt, 2004). Younger, highly active officers may self-select into specialized units that encourage more police-civilian contact (see Moskos, 2008, p. 137). Indeed, the goal of specialized units (e.g., drug squads, gang units) is to make arrests, as such, specializing may foster competition (e.g., number of arrests, effectiveness) among units leading to the abuse of power (Skolnick & Fyfe, 1993). Likewise, officers in specialized units may be assigned to areas where force is more likely (Toch, 1996) or tasked with policing groups of civilians that are perceived to be most deserving of police attention (e.g., gang members). Whereas,
others have argued for the benefits of continued and repetitive exposure to various situations over time, with exposure having a positive impact on how officers “handle” civilians and manage conflict in their encounters with the public over time.

Depending on how force is measured, the relationship between officer experience and force generates mixed results. Examining the predictors of police use of force along a continuum, Crawford and Burns (1998) found that officer age was unrelated to an officer’s propensity to use any type of force, challenging Garner et al.’s (2002) findings that older officers, when they elect to use force, are likely to use less severe force in comparison to younger officers. Similarly, findings by Sun and Payne (2004), Lawton (2007), McCluskey and Terrill (2005), and several others find no association between years of experience and the likelihood of police use of force.

*Education.* Related to experience is this emphasis on education with performance-related differences between college-educated and non-college-educated officers linked to use of force behaviors. While there has been a history of advocacy in America with various Advisory Commissions calling for the employment of more college-educated officers (President’s Commission on Law Enforcement and the Administration of Justice, 1968; National Advisory Commission on Criminal Justice Standards and Goals, 1973), a college degree has yet to become a requirement for qualification with only 1% of local police departments in the United States requiring a 4-year college degree (Hickman & Reaves, 2006). Instead, a college education is used as an informal requirement for hiring and advancement (Carter & Sapp, 1990). The push for higher education in policing has rested on the assumption that college-educated officers are more effective in handling the complexities of their day-to-day tasks, such that they are equipped with the propensity and
mannerisms to perform better and more responsibly on the job (Aamodt, 2004; Carter & Sapp, 1990; Shjarback & White, 2016; Walker, 1977; White, 2001).

Likewise, a college education is perceived to foster qualities that encourage greater self-control, awareness, and a “liberal” attitude that decreases dogmatism and prejudice (Feldman & Newcomb, 1969; Wilson, 1986). It has been suggested that college-educated officers are likely to hold less authoritarian beliefs (Dalley, 1975; Sherman & Blumberg, 1981), are less likely to be rigid (Roberg, 1978), punitive (Guller, 1972), and place more emphasis and value on ethical behaviors (Shernock, 1992). These officers are also perceived to have better decision-making skills (Worden, 1990), be more effective verbal communicators (Carter & Sapp, 1990; Sterling, 1974; Worden, 1990), and have a greater appreciation and understanding of the implications of coercive use of force (Paoline & Terrill, 2007). In sum, highly educated officers are likely to receive higher ratings from their superiors (Aamodt, 2004; Carter & Sapp, 1990), receive fewer civilian complaints (Aamodt, 2004; Cohen & Chaiken, 1972; Shjarback & White, 2016), fewer excessive use of force complaints (Cascio, 1977), sustain fewer injuries from assaults (Cascio, 1977; Cohen & Chaiken, 1972), and appear to use force less often (Paoline & Terrill, 2007; Terrill & Mastrofski, 2002).

However, even with this push for education, the link between education and police behavior is not consistent. For example, Rydberg and Terrill (2010) examine education's effect on three outcomes: arrest, search, and force. Using data from the Project on Policing Neighborhoods in Indianapolis, Indiana and St. Petersburg, Florida from 1996 to 1997, they find that college education significantly reduces the likelihood of use of force (also see Aamodt, 2004; McElvain & Kposowa, 2004; Terrill & Mastrofski, 2002) with officers
with some college exposure significantly less likely to use force. However, attending college did not significantly influence other coercive behaviors such as searches or arrest behaviors. To this send, Paoline and Terrill (2007) argue that college exposure may not be enough to significantly reduce coercive behaviors; instead, the completion of a 4-year program tends to be most beneficial, whereas Sun and Payne (2004) find that officers' education level did not influence the likelihood of using force.

*Personality traits.* Finally, a range of social and psychological factors have also been used to explain variations in force. Skolnick (1967) and Niederhoffer (1967) described the police officers “working” personality as dominated by cynicism, mistrust, and suspicion. It has been suggested that policing both attracts and fosters individuals with a remarkably intolerant, dogmatist, conservative, and aggressive personality type (Carlson & Sutton, 1975; Smith et al., 1970; Teasley & Wright, 1973). Namely, “authoritarianism” has been related to hostile police attitudes, use of force, and officer misconduct (Black, 1972; Genz & Lester, 1976; Smith et al., 1967). For example, Black (1972) contends that officers that are predisposed to use force and to misuse force have authoritarian, punitive personalities (Henkel et al., 1997; Toch, 1996; Wortley, 2003) that are likely to stem from undesired police activity (Teasley & Wright, 1973). Authoritarian attitudes are likely to concentrate amongst officers tasked to high crime areas as opposed to those in more administrative roles (Genz & Lester, 1976), and in departments where a traditional, more conservative, style of police is employed (Brown & Willis, 1985; Burbeck & Furnham, 1984; Carlson & Sutton, 1975; Carlson, 1971).

Force and officer misconduct have also been associated with antisocial tendencies such as low self-control (Blumberg et al., 2016; Donner et al., 2016; Donner & Jennings,
Using a sample of 1,935 police officers from the Philadelphia Police Department, Donner, and Jennings (2014) examined the relationship between low self-control, comprising nine behavioral (e.g., impulsive, short-sighted, risk-taking, an inability to delay immediate gratification) and police misconduct. They found that low self-control was associated with officers having a history of civilian complaints about physical abuse, having a history of civilian complaints about verbal abuse, being the subject of internal affairs investigations, and general misconduct.

Findings specifying a distinct “police personality” are vague at best, with many studies (see Bayley & Mendelsohn, 1968; Brown & Willis, 1985; McNamara, 1999; Niederhoffer, 1967; Smith et al., 1967) finding no evidence of a remarkably intolerant, conservative or aggressive personality in policing. Instead, it has been suggested that police recruits in the academy demonstrate significantly higher integrity scores and show more significant commitment to social responsibility and service (Schlenker, 2008; Schlenker et al., 2008; Sherman & Blumberg, 1981). Moreover, the empirical evidence itself is mixed on what a police personality is and whether there is a pre-existing “condition.” For example, whether specific individuals who display particular personality profiles select into or are socialized by the force, such that personality profiles are in part due to socialization in the academy, and on the job (Blumberg et al., 2016; Twersky-Glasner, 2005).

Indeed, it is more convincing to think of the “police personality” as a hybrid of select personality traits and occupational socialization strongly characterized by a police culture. Most police departments do a relatively thorough job at screening out individuals who exhibit certain personality traits. Indeed, most recruits display somewhat similar
personality profiles as they enter the profession (Burbeck & Furnham, 1984; Ho, 2001). However, personality traits are dynamic (Kelly, 1955); they continually develop and change with stimuli and experiences. Thus, it is likely that an officer’s experiences (good or bad) throughout their careers -- via occupational elements of the job such as the need to maintain personal safety and maintain public order -- facilitates, shapes, and further reinforces their “personality profiles” and interactions with civilians (Mastrofski et al., 2000; Twersky-Glasner, 2005).

Police use of force – a cultural, social, and networked perspective

Police culture

In his seminal ethnography of police officers in Gary, Indiana, Westley (1953, 1970) introduced the term police culture into standard policing nomenclature. The role of police culture is critical for understanding the system of values and attitudes that define police officers' social world (Bittner, 1970; Manning, 1977; Skolnick, 1966; Westley, 1970; Worden, 1995). Aspects of the police occupation such as dangers on and off the job, authority (e.g., capacity to use force), and a preoccupation with efficiency and certainty enable officers to develop a recipe of rules that guides their behaviors and helps them collectively cope with the strains that stem from the workplace (Bittner, 1970; Kappeler et al., 1998; McNamara, 1999; Paoline 2003; Reuss-Ianni & Ianni, 1983; Rubinstein, 1993; Van Maanen, 1978a; Westley, 1970). Notably, it is this “shared” aspect that links occupational and organizational elements of policing to the behaviors of officers (Ingram et al., 2014; Paoline, 2003), with more recent works defining the theoretical boundaries of what the “police culture” entails (Crank, 1998; Paoline, 2003).
Historically, accounts of “traditional police culture” have stemmed from the occupational and organizational aspects of police work. Within the occupational framework itself, police work has two attributes that unify officers and separates them from the public. These are 1) the inherent dangers of the profession (Barker, 1977; Cullen et al., 1983; Kappeler et al., 1998; Sierra-Arévalo, 2016; Sparrow et al., 1990; Toch, 1996); and 2) the ability to exercise coercive power and authority over the public (Banton, 1964; Bittner, 1970; Manning, 1977; Reiner, 1985). Officers are tasked with maintaining public order and safety by engaging with civilians in a variety of contexts, yet they embrace these interactions with inherent suspiciousness, distrust (Manning, 1977; 1995; Skolnick, 1966; Westley, 1970), and coercive authority (Bittner, 1970; Brown, 1988; Van Maanen, 1974). While these elements increase loyalty between officers, it promotes a relatively cautious, negative, and cynical view of non-officers (i.e., civilians), enabling a “us vs. them” mentality (Banton, 1964; Bittner, 1970; Britz, 1997; Terrill et al., 2003).

The officers’ working environment also generates a host of stressors like those experienced on the street (Cooper, 2012; Crank et al., 2007; Crank & Caldero, 1991; Drummond, 1976). For example, organizational elements such as unpredictable and punitive oversight by upper management and supervisors (Brown, 1988; Engel, 2000; McNamara, 1967; Skolnick, 1966), negative views of supervision (Reuss-Ianni & Ianni, 1983; Van Maanen, 1974; Worden, 1995), and characteristics of the “officer role” – which is relatively ambiguous and multidimensional - affords officers the discretion to act, but to do so in a manner that aligns with departmental norms (Walker, 1977). When coupled together, the organizational and occupational elements of police works encourages officers to isolate themselves from the public while establishing more robust bonds with peers who
can provide mutual loyalty and “support in the face of a hostile citizenry and a punitive bureaucracy” (Paoline et al., 2000, p. 579).

**Socialization into police culture**

Police culture breeds a peer-group mentality, albeit to varying degrees, such that normative or problematic police behaviors are likely to be socialized on the job (Van Maanen, 1974) and among those in shared environments. Several seminal works call attention to the social milieus where culture is likely to flourish and transmitted among officers. In *Justice Without Trial*, Skolnick (1966) argues that the shared threat of danger leads officers to band together and form tight-knit ‘brotherhoods’ characterized by cohesion and solidarity (also see Brown, 1988; Muir, 1977). This is because officers in a shared environment who come in regular contact with one another are exposed to similar populations and crime levels (Crank, 1998; Moon & Zager, 2007), beliefs about the police role (Brooks et al., 1994; Sun, 2003), and types of bureaucracies and supervision (Crank, 1998, 2003; Ingram et al., 2014; Paoline, 2003).

The “shared aspect” of policing cultivates interdependencies among officers as it exposes officers to 1) everyday situations and provides a means to cope with the problems associated with policing, 2) prescribes officers the opportunity to rationalize, neutralize and justify their own behaviors as well as that of their peers (Kappeler et al., 1998; Waegel, 1984) and 3) constrains officer attitudes and beliefs through a common chain of command (Chappell & Piquero, 2004; Ingram et al., 2013, 2018; Savitz, 1970). The view that officers' actions are a product of their social milieu, rather than their personality profiles, has become a core premise of policing and summarized by Niederhoffer (1967), “it is the police
system, not the personality of the candidate, that is the more powerful determinant of behavior and ideology” (p. 160).

Scholars have turned to sociological and criminology explanations (e.g., social learning theory, opportunity theory, differential association theory) to highlight the role (and importance) of peers in the workplace to understand the mechanisms for which officer attitudes and behaviors are learned and transmitted (Chappell & Piquero, 2004; Kappeler et al., 1998; Savitz, 1970). Across these perspectives, behaviors, much like other forms of crime and delinquent activities, are learned through social interactions, and in association, with peers who share similar attitudes, norms, and values (Haynie, 2002; Reiss & Farrington, 1991; Tremblay, 1993; Warr, 2002; Warr & Stafford, 1991; Weerman, 2003).

Indeed, because officers are responsible for each other’s safety, there is this natural tendency to form bonds, and thus form an organizational culture that breeds a peer-group mentality whereby officers learn and exchange definitions favorable to their group identity (Alpert et al., 1997; Chappell & Piquero, 2004; Kappeler et al., 1998). For example, Savitz (1970) applied social learning theory to examine recruits’ trajectory from the Philadelphia Police Department as they advanced from the police academy and onto the streets. Savitz (1970) found evidence of “deep ties of loyalty” (p. 695) driven by a “big brotherhood” among officers (p. 699). Indeed, in the first three years on the job, recruits become increasingly socialized into their occupational role and police culture. They increasingly adopted the value system (e.g., became more cynical) of older, more experienced officers with whom they worked on a day-to-day basis and were more tolerant of officer-driven deviance. Likewise, Chappell and Piquero (2004) aimed to understand how peers influenced police misconduct. In their sample of 499 Philadelphia police officers, Chappell
and Piquero (2004) found that officers who believed that their peers would rationalize and treat deviant behaviors, such as excessive use of force less seriously, were more likely to have misconduct complaints filed against them.

Together, findings reveal that various forms of workplace conduct are shared through officers’ interactions and exposure to common features of their working environments. However, findings also demonstrate that police culture is not a “monolithic phenomenon shared by all officers” (Ingram et al., 2013, p. 366). Static and homogeneous measures of the policing working environment ignore the heterogeneous and dynamic nature of officer social ties. Taking a cue from research on crime and deviance more broadly – which has consistently demonstrated that most crime is committed by a subset of individuals (e.g., chronic group offenders) (Brandl et al., 2001; Brandl & Stroshine, 2013; Harris, 2010; Kennedy, 1996; Piquero et al., 2007) and committed in the company of others (Reiss & Farrington, 1991; Tremblay, 1993; Warr, 2002; Warr & Stafford, 1991; Weerman, 2003) - scholars have recently tapped into network analysis to directly overcome the limitations hampering research on police behaviors, and specifically coercive authority. Network analysis, which systematically maps out the set of social interactions, has led to meaningful advances in the group nature of the crime, testing key propositions about groups’ organization and how these structures impact behaviors (Haynie, 2001). For this reason, the propensity and frequency of peer interactions have been central in the study of deviant and non-deviant behaviors (Conway & McCord, 2002; Haynie, 2001, 2002), though the policing literature has been slower to seize a network approach to model the set of interactions between officers.
Network theory and group processes

The structure of police agencies and the social mechanisms that drive the adoption of behaviors suggests that officer networks may play a key role in understanding the prevalence and transmission of behaviors in the policing work environment. Social network analysis provides a theoretical, visual, and analytical understanding of the social and structural makeup of relations. Network theory focuses on the interdependent nature of relations (or other units); theorizing on the context of relations, how relations are fostered, and the outcome of such relations, further adding to our understanding of social learning theory (Akers, 1985), differential association theory (Sutherland et al., 1995), collective efficacy (Sampson et al., 1997) and social disorganization theory (Sampson & Groves, 1989). Furthermore, network analysis provides a means to systematically and analytically uncover the interconnectedness of a group(s), who is tied to whom, the role of individuals, central individuals in the network, as well as a means to delineate group boundaries and disentangle selection and influence effects in criminal and non-criminal networks.

The use of formal network methods to understand patterns of deviant and non-deviant behaviors has a long-standing tradition in sociological and criminology research (for reviews, see Bouchard & Malm, 2016; Faust & Tita, 2019; Haynie & Kreager, 2013; Papachristos, 2011). Network analysis has been applied to understanding peer relations in organizations such as schools, prisons, and the workplace (Haynie, 2001, 2002; Labun et al., 2016; McGloin & O’Neill Shermer, 2009; Schaefer et al., 2017; Sparrowe et al., 2001). Many of these studies highlight the utility of understanding how social relations are selected and fostered over time and how network structure can collectively shape and
disentangle the behaviors, movements, and the position of those in the network (Gould, 1993; Schaefer, 2018).

Specifically, network methods can lend support for social influence in the policing work environment, not only providing evidence that peers may serve as social conduits through which behaviors are learned and transmitted (also see Britz, 1997; Chappell & Piquero, 2004; Getty et al., 2016; Ingram et al., 2014, 2018) but also describing how network structure can influence such behaviors. For example, in larger organizations, network analysis uncovers hidden and opaque patterns of interactions, providing insight into the underlying structure of relationships while identifying areas that may be highly resilient, adaptive, or vulnerable to change (Duijn et al., 2014; Morselli & Roy, 2008). This is especially useful for determining how networks, or subgroups within more extensive networks, may react to (re)organizations following larger external interventions (e.g., new policy or procedures) or smaller operational changes (e.g., shift changes, partner changes, removal of officers). While many perspectives implicitly signal a “network” theory of police use of force - for example, the extent to which officers’ attachments to the occupation and the peer group relate to improper use of force - they rarely have applied network methods to systematically and empirically test these theories.

**PLANNED ANALYSIS**

Although most explanations have focused on the situational, organizational, and officer level for understanding the causes and correlates of police use of force, excessive use of force, and misconduct, they have done so at the expense of overlooking the group dynamics and network position of officers. These intricacies are at the center of theorizing how officers behave towards civilians and the coercive authority that officers display over
civilians. Namely, that police culture itself is associated with inappropriate and aggressive behaviors, police abuse, excessive and illegal use of force, and misconduct (e.g., social learning among officers) (Roithmayr, 2016; Skolnick & Fyfe, 1993; Terrill et al., 2003; Westley, 1970), though previous studies have lacked quantifiable metrics to understand the mechanisms for how peer relationships foster such behaviors. Conversely, more recent studies that have adopted a network approach - applying quantifiable metrics - to understand the group nature of policing have looked at more extreme outcomes such as misconduct and excessive use of force. This study applies a similar approach but looks at a more widespread practice on the street - use of force - that may or may not lead to actual abuses of force.

This research is driven by three lines of inquiry to understand the structure and patterns of force behaviors reported by officers in New Jersey. The first study is mostly descriptive, supplemented with a network approach to understand police partnerships. It evaluates which and whether officer-level attributes and larger network properties are associated with the likelihood of officers selecting to use force together. The second study adopts a group-level perspective to uncover patterns of force within and between officers in a shared working environment, where group boundaries are delineated by officers in the same department. This study evaluates whether departments' organizational and structural composition is associated with specialization or versatility in force behaviors. The final study identifies focal officers through a singular measure of network capital. Compared to their peers, focal officers have high-risk profiles, such that they repeatedly employ force and doing so with a larger network of peers. These officers are situated within densely knit
“local groups” to determine their structural position within the broader use of force network.

OVERVIEW OF DATA

Use of Force Policy in New Jersey

As part of the New Jersey Attorney General’s Use of Force Policy (2000; 1985), the New Jersey Use of Force Advisory Committee provides policy guidance to prepare officers employed in the state of New Jersey to react appropriately in use of force situations. The report defines and outlines various types of force, training requirements, the duty to intervene, and inappropriate uses of force, such as deadly force. While the study focuses on the Attorney General’s basic guidelines, it is essential to note that agencies and departments across the state can and may vary in their use of force practices, posing additional requirements or limitations on force.

The policy report, however, sets forth two general directives. First, all officers employed in the state of New Jersey are required to attend semiannual training sessions. These training requirements must provide instructions on the lawful and appropriate use of force and deadly force. Training must also reflect current standards established by statutory and case law, county, and individual agency policy. Second, officers have a duty to intervene. The report requires that all department members control, prevent, stop, or “interrupt the flow of events” before fellow officers resort to illegal or inappropriate use of force and prevent instances where force against a subject becomes excessive.

Defining force

According to the Attorney General's Use of Force Policy (2000; 1985), officers in the state of New Jersey are authorized to “use physical force or mechanical force when the officer reasonably believes it is immediately necessary at the time”: 

a. to overcome resistance directed at the officer or others; or
b. to protect the officer, or a third party, from unlawful force; or
c. to protect property; or
d. to effect other lawful objectives, such as to make an arrest.

However, the report states that use of force should be limited. Namely, officers must exhaust all other reasonable alternatives before resorting to force. If situations where force is necessary arise, the report explicitly states that officers must resort to using the minimum degree of force required to make a lawful arrest.

... “In situations where law enforcement officers are justified in using force, the utmost restraint should be exercised. The use of force should never be considered routine. In determining to use force, the law enforcement officer shall be guided by the principle that the degree of force employed in any situation should be only that reasonably necessary. Law enforcement officers should exhaust all other reasonable means before resorting to the use of force. It is the policy of the State of New Jersey that law enforcement officers will use only that force which is objectively reasonable and necessary.”

Though the Attorney General's Use of Force Policy (2000; 1985) does not specify a specific force continuum, it provides guidance and direction to officers in the state with provisions that define the types of force/weapons used to respond to particular types of resistance. Specifically, the policy report outlines five types of authority (constructive authority, physical contact, physical force, mechanical force, and deadly force). It provides examples that include what constitutes force and when force may be used (see Appendix 1). It poses restrictions on the use of deadly force and firearm use. In addition to the
Attorney General's Use of Force Policy, each agency may place additional requirements or limitations on force used. For comparison purposes, see Appendix 2 for an outline of how the Jersey City Police Department defines authority and force.

**Reporting force**

In instances where *physical, mechanical, or deadly* force is used, each officer who uses force must complete a Use of Force Report (see Appendix 3), or an agency required format (see Appendix 4 for the Jersey City Police Department’s Use of Force Report). In instances where deadly force results in death or serious bodily injury, or when use of a firearm by a law enforcement officer leads to injury, officers are required to report to county prosecutors. County prosecutors and state law enforcement agencies must then notify the Division of Criminal Justice within 24 hours. Additionally, county, and municipal law enforcement agencies must report physical, mechanical, or deadly force annually to both the county prosecutor and the Division of Criminal Justice director.

**The Force Report**

Data for the dissertation are drawn from the Force Report, a centralized database of police force reports across municipal police departments in New Jersey, and the New Jersey State Police from 2012 to 2016. The Force Report stems from a 16-month investigation by NJ Advance Media for NJ.com ([http://force.nj.com/](http://force.nj.com/)). Nearly two decades ago, the New Jersey Attorney General’s Office mandated that officers who employ physical, mechanical, or deadly force complete a force report specifying the nature and context of force used. The larger goal was to create a centralized database that would identify problematic officers, departments, and trends. While a centralized database was never implemented, a landmark New Jersey Supreme Court ruling in July 2017 made these reports fully available to the
public. Through a series of OPRA requests, NJ Advance Media filed 506 public records requests and collected over 70,000 use of force forms from January 1, 2012, through December 31, 2016. The Force Report includes 461 municipal police departments and the State Police in New Jersey. To date, it is considered to be the most comprehensive statewide database of police force in the U.S.

Despite the comprehensiveness of these data, it is important to note several issues. First, there are variations in statewide guidelines for reporting force. For example, while some departments or officers may be more rigorous about reporting, others may not. This is reflected in the numbers, with some departments reporting a higher number of entries, whereas others do not. Second, missing data may be random or non-random. The news organization reported instances where the records were blackened due to age or nearly illegible, missing key details, under quarantine for mold contamination, merely incorrect, or never completed. While NJ Advance Media took extra steps to obtain additional records with requests placed to prosecutors' offices and the Attorney General's Office, the cause of missing data across all cases is unknown.

NJ Advance Media hired a third-party, Invensis, to transcribe and electronically enter reports into a spreadsheet. In doing so, they accepted an error rate of 2% (McCarthy & Stirling, 2019). This was due to two reasons: 1) inconsistencies in forms used by different departments, and 2) a general understanding that these reports are self-reported and rely on the reporting officer's accuracy. To reduce human errors in entering reports, reporters consulted with independent experts for input, developing a review system that would minimize other errors during data entry. After each day, 2% of the daily batch of

---

forms were selected for a daily audit. These forms and data points were cross-validated with their original records by a team of six reporters. In cases where there were discrepancies in how data were inputted, the news organization discussed the errors with Invensis, and forms were re-entered correctly. In addition to these daily audits, the team conducted monthly audits to identify subsequent problems. In total, the audits revealed a 0.6% error rate, below the 2% benchmark set by the organization.

The next step resulted in cleaning and standardizing these data into a master database. Namely, NJ Advance Media standardized how incident times, incident dates, town names, officer level attributes, subject level attributes, and entries for criminal charges were recorded. Officer names were manually checked for spelling errors, inconsistencies, and incorrect entries. Additionally, these were cross-validated with badge numbers, state pension records, and news archives in cases of errors. Each officer was assigned a unique ID in relation to their first name, last name, and police department. This helped prevent errors in instances where officers in separate departments had the same name. It also ensured standard analysis in cases where a single incident of force involved multiple officers. Each incident was also assigned a unique ID with duplicate entries identified and removed. Finally, the “nature of force” was standardized with checkboxes on the forms: compliance hold, hands/fists, chemical agent (pepper spray), strike/use of baton, or “other” object. Kicks/feet were grouped in with “knee strikes” and changed to “leg strikes.” Any uses of “wrestle to the ground” or “takedown” were reversed to “tackle/wrestle to the ground.” Any incidents of force that involved animals were removed.

In addition to the changes aforementioned by NJ Advance Media, all data were further validated and checked for accuracy. Given that social network analysis relies
heavily on unique identifiers, officer names and supervisor names were manually validated and further standardized, if necessary, to reflect their unique IDs. Officers were matched on any non-missing indicators such as their first name, middle name, last name, sex, race, badge number, approximate years of experience (relative to the year the incident was reported), and county. In cases where officer names were misspelled (e.g., letters were mixed up, a letter or two were missing, or names were misspelled) or instances where the same officer had moved departments (i.e., same officer, different departments) but matched on a host of other variables, such that they were treated as separate entries, their unique IDs were merged. Appendix 5 provides a list of relevant variables obtained from the Force Report aggregating indicators at the incident level, officer level, and civilian (i.e., subject) level.

Data overview

Figure 1 provides an overview of how data are nested. Appendix 6 aggregates the number of departments, unique supervisors (i.e., supervisor who signed the report), unique officers, use of force incidents, and use of force reports by county. Over the five years, there were 17,845 unique officers involved in 43,389 unique use of force incidents across the state of New Jersey from 2012 to 2016.
Each officer involved in an incident where they elected to use force must complete a use of force report in New Jersey. As officers could be involved in multiple force incidents, there was 69,194 use of force reports filed from 2012 to 2016. Figure 2 provides the distribution of unique force incidents – that is, a count of unique incidents (i.e., events) where force was used, regardless of how many officers were involved and the number of force reports filed by an officer from 2012-2016. On average, there was 8,548 (SD = 117) use of force incidents per year, with the number of force incidents slightly peaking in 2014. Conversely, there were, on average, 13,687 (SD = 520) use of force reports filed per year, with the number of reports slightly peaking in 2016.

3 Though officers could be involved in multiple force incidents, “unique officers” entails a count of officers involved in at least one use of force incident from 2012 to 2016. For example, if Frank John were involved in six use of force incidents, and thus completed six use of force reports, he would only be counted as 1 officer.
4 Each officer involved in a force incident is required to complete a use of force report. “Unique incidents” entails a count of incidents where force was use. For example, if six officers were involved in two separate incidents, this would entail six force reports, and two force incidents.
Figure 2. Frequency of use of force incidents and force reports filed by the year

Figure 3 provides the distribution of the number of officers involved (i.e., number of force reports) per use of force incident (n= 43,389). On average, each force incident involved 1.59 officers (SD = 0.90), with most incidents involving one officer, whereas other incidents involved 12 officers.

Figure 3. Number of officers involved in a use of force incidents, incident level
Finally, at the officer level, from 2012 to 2016, of the 17,845 officers, 36% (n=6,336) filed only one use of force report, 18% (n=3,271) filed only two use of force reports, 12% (n= 2,084) filed three use of force reports with the remaining 3% (n= 6,154) of officers filing four or more use of force reports. Figure 4 provides the complete distribution of reports filed per officer. On average, each officer across these data filed four use of force reports (SD = 4.54) with a range of 1 to 61.

![Figure 4. Number of force reports filed per officer, officer level](image-url)

Table 1 provides a descriptive summary of officer-level attributes in addition to the frequency of reports signed by a supervisor.
Table 1. Officer Attributes, New Jersey 2012-2016

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Officernumber</td>
<td>17,845</td>
</tr>
<tr>
<td>Officer gender (<em>time-invariant</em>)</td>
<td></td>
</tr>
<tr>
<td>% Male</td>
<td>72.54</td>
</tr>
<tr>
<td>% Female</td>
<td>4.76</td>
</tr>
<tr>
<td>% Unknown/Missing</td>
<td>22.71</td>
</tr>
<tr>
<td>Officer race/ethnicity (<em>time-invariant</em>)</td>
<td></td>
</tr>
<tr>
<td>% White</td>
<td>61.14</td>
</tr>
<tr>
<td>% Hispanic</td>
<td>7.06</td>
</tr>
<tr>
<td>% Black</td>
<td>6.93</td>
</tr>
<tr>
<td>% Asian/Pacific Islander</td>
<td>0.84</td>
</tr>
<tr>
<td>% Other</td>
<td>0.24</td>
</tr>
<tr>
<td>% Unknown/Missing</td>
<td>23.80</td>
</tr>
<tr>
<td>Officer experience (tenure), years (<em>time-variant</em>)</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>8.66 (SD = 6.41)</td>
</tr>
<tr>
<td>Range</td>
<td>1-43</td>
</tr>
<tr>
<td>25th percentile</td>
<td>75th percentile</td>
</tr>
<tr>
<td>% Unknown/Missing</td>
<td>21.49</td>
</tr>
<tr>
<td>Officer rank (at the time of the report) (<em>time-variant</em>)</td>
<td></td>
</tr>
<tr>
<td>% Officer</td>
<td>85.98</td>
</tr>
<tr>
<td>% Other</td>
<td>14.02</td>
</tr>
<tr>
<td>% Sergeant</td>
<td>5.24</td>
</tr>
<tr>
<td>% Detective</td>
<td>3.27</td>
</tr>
<tr>
<td>% Trooper (State Law Enforcement Officer)</td>
<td>1.60</td>
</tr>
<tr>
<td>% Other</td>
<td>3.91</td>
</tr>
<tr>
<td>N Supervisors (unique), (<em>time variant</em>)</td>
<td>6,490</td>
</tr>
<tr>
<td>% Force Reports with supervisor signed</td>
<td>76.54</td>
</tr>
<tr>
<td>% Unknown/Missing</td>
<td>23.46</td>
</tr>
</tbody>
</table>
STUDY 1. THE SOCIAL STRUCTURE OF OFFICER NETWORKS AND POLICE PARTNERSHIPS

The killing of George Floyd in Minneapolis, in many ways, is symbolic of police abuses across the country. Floyd, a 46-year-old Black man, was approached by four officers responding to a call about a fake twenty-dollar bill. The encounter became charged and quickly escalated with a fatal knee-to-neck restraint. Three other officers stood by as bystanders, collectively and continuously, ignoring Floyd’s pleas that he could not breathe. While not isolated, this incident continued to reignite public attention to police brutality in the United States - advancing widespread calls for defunding the police, police reform, and accountability on the part of officers, especially those on the scene, but failed to intervene. The shift in response also redirected attention to an important issue: how the “shared aspect” of police work contributes to systematic patterns of police use of force and police violence.

The policing profession’s structural and interdependent nature presents a particularly novel environment to employ network analysis. First, police behaviors are guided by a set of formal and informal organizational and occupational rules. Second, officers are assigned to patrol areas based on districts, unit/beats, or specialized skills. Thus, they are limited in whom they interact with and whom they come in contact with. This is particularly salient given that most of an officer’s time and energy is spent with their colleagues (e.g., shift partners) under intense public and organizational scrutiny. Third, there is this inherent, unspoken expectation of mutuality and reciprocity, where colleagues allot greater degrees of trust and responsibility to one another. This dimension of “loyalty” and “trust” far surpasses any other working profession and reflects ideals found in networks of family and friends (Conti & Doreian, 2010; Kleinig, 2000). Finally, the
degree of exposure and frequency of interactions prescribes officers the opportunity and
the environment to learn social norms from one another with select officers (e.g., informal
mentors, supervisors, field training officers) likely to exert substantial influence on the
behaviors of others (Getty et al., 2016; Moskos, 2008; Skolnick & Fyfe, 1993).

Building on the “shared aspect” of police work, the current study provides insight
into patterns of police use of force by examining the dynamics of officer partnerships.
Specifically, it explores the grouped nature of police use of force by investigating whether
1) police use of force is grouped behavior, 2) officers are likely to use force together if they
share a colleague who has also used force, and 3) officers with similar demographic
attributes are likely to use force together?

**Officer networks and police behaviors**

Some of the first applications of network analysis to policing highlight the interdependent
nature of police work, finding that the frequency of interactions between officers predicted
the degree to which they developed shared beliefs, attitudes, and behaviors. For example,
a study by Pastor and Mayo (1995) examined leadership in a campus police organization.
Officers provided information about their social interactions with other officers in the
organization and evaluated members’ behavior. Officers in the core of the network – that
is, those who frequently connected and socialized with one another - shared more similar
beliefs, attitudes, and behaviors than those who were less connected (Pastor & Mayo,
such as proximity and centrality for understanding social influence and relationships in a
police organization. More recently, drawing on networks to understand socialization in the
police academy, Conti and Dorein (2009) examined how the academy’s social
infrastructure (e.g., division into squads, social partners, seating arrangements) impacted racial integration and social relationships among recruits. Network data on 68 recruits collected at three-time points, representing a distinct academy training phase, revealed a strong relationship between social proximity and social relations in the academy. Irrespective of race, both joint squad membership and adjacent seating assignments (though to a lesser degree) enhanced social knowledge and friendship formation among recruits and increased in intensity over time. Their findings emphasize the importance of informal networks instead of race-based or formal training protocols for promoting prosocial behaviors among officers in the police academy.

Turning to the mechanisms behind the “grouped” nature of police violence and misconduct, Roithmayr (2016) argues that networks matter for understanding the social transmission of coercive behaviors among officers. Roithmayr (2016) argued that the excessive use of force “spreads and escalates” over time and space (p. 407). Drawing from research on criminal groups, victimization, and social network analysis, Roithmayr (2016) suggests that excessive police use of force goes beyond explanations at the individual, organizational, and situational level; instead, Roithmayr (2016) argues that force is contagious with officers learning, reinforcing, and neutralizing such behaviors. Specifically, because police officers are subjected to peer influence and control, officers are likely to employ force if they feel that their behaviors 1) will be neutralized or rewarded by their colleagues and 2) align with the beliefs and activities of their colleagues (Alpert & Dunham, 2004; Fagan & Geller, 2015; Hunt & Manning, 1991; Klockars, 1984; Roithmayr, 2016; Waegel, 1984).
Providing three of the most compelling empirical demonstrations of the role of networks in structuring officer misconduct are studies by Quispe-Torreblanca and Stewart (2019), Ouellet et al. (2019), and Wood, Roithmayr, and Papachristos (2019). Quispe-Torreblanca and Stewart (2019) used four years of allegations of misconduct involving 49,403 sworn officers and staff employed by the London Metropolitan Police Service. Linking officers and staff through their shared line managers, the authors demonstrated that an individual’s network structured the likelihood of being named in a complaint. Even after controlling for a host of covariates such as the proportion of male peers, the proportions of peers for each rank, performance rating, the average length of service, yearly and seasonal controls, Quispe-Torreblanca and Stewart (2019) found a positive relationship between the proportion of peers with a history of misconduct and ones’ likelihood of misconduct. They estimated that a ten-percentage point increase in the fraction of peers with misconduct increased one’s incidence of misconduct by 8%. This effect holds irrespective of officer turnover with officers changing groups or receiving new group members. They argued that officers’ local networks produce rationalizations and neutralizations to engage/endorse deviant behavior while also providing context for officers to conform to group norms (Hunt & Manning, 1991; Waegel, 1984).

A similar conclusion was drawn by Ouellet et al. (2019). Reconstructing officers’ misconduct networks in the Chicago Police Department (CPD) by officers who had been named in a complaint together, Ouellet et al. (2019) examined the records of 8,642 sworn police officers involved in multiple reports of misconduct (2 or more) from 2007 to 2015. They found that net of officer attributes and differential exposure to high crime neighborhoods, police officers who had a greater proportion of colleagues named in prior
use of force complaints were more likely to generate excessive force complaints. Specifically, a 39-percentage point increase in the fraction of peers with prior use of force complaint increased the risk of an officer receiving a future use of force complaint by 26% compared to an officer whose peers did not engage in prior use of force.

More recently, Wood, Roithmayr, and Papachristos (2019) were able to disentangle whether network structure and select officer partnerships (e.g., officers that share the same race or were similar in age) drove incidence of misconduct in Chicago over six years. Based on 16,503 department and civilian filed complaints, their results found that police misconduct was not distributed evenly but concentrated on a small number of officers. For example, at the network level, they found that “the top 1 percent of officers have received a civilian co-complaint with 26 other officers on average” (Wood et al., 2019, p. 13). Most misconduct complaints were filed against two or more officers, with 83% of officers named alongside at least one other officer in civilian complaints and 71% of officers named alongside at least one other officer in departmental-based complaints. Most notably, they found that misconduct was likely to occur between some pairs of officers over others. For example, officers who had similar years of experience were more likely to engage in misconduct together, and despite receiving a similar number of complaints, Black (relative to White or Hispanic) officer pairs were more likely to be the subject of civilian and departmental complaints compared to a racially heterogeneous officer pair.

Despite this recent uptake of research on officer networks, few studies have analyzed the network structure of police use of force. Most evaluations of police use of force and violence have been limited to officer-level, departmental-level, and situational-level characteristics, without much consideration given to the social similarities and spatial
proximity of officers who work together, and thus, evidently, come to use force together. Indeed, while the use of force network is only a subset of the larger network that the officer is embedded in, these ties demonstrate systematic behaviors that can uncover underlying relational patterns. These interactions may signal the emergence and diffusion of excessive use of force events, misconduct, or elevated levels of police violence, more broadly.

Building on prior research, the current study examines whether (and which) officer-level attributes and social processes that lead to the observed network structure are associated with officers selecting to use force together. The goal is to understand: 1) whether some officers select to use force together whereas others do not, and 2) are observed ties between officers arranged in a particular way, and 3) if officer attributes impact the likelihood that officers use for together.

Data and Methods

Exponential Random Graph Models (ERGMs) are used to evaluate whether patterns and frequency of force are transmitted through officer partnerships. Figure 5 maps the use of force (i.e., co-involvement in force) network(s). The grey nodes represent individual officers, whereas a blue tie (i.e., edge) indicates that officers were involved in at least one use of force incident together. The network on the left represents all officers involved in at least one incident with one other officer. This network comprises 14,512 of the 17,845 officers and 32,272 ties between officers. The network on the right represents the largest connected component. The largest connected component is a subset of the network where every node (i.e., officer) is reachable via some path by every other officer (Papachristos, Braga, et al., 2015; Roberto et al., 2018). The largest connected component of the use of force network comprises 3,819 officers and 10,712 ties between officers. It comprises 21%
of all officers who filed a force report, 27% of all use of force incidents, and 29% of all force reports filed in New Jersey from 2012 to 2016.

Note. Left: The co-involvement network 2012-2016 with isolates removed (n officers=14,512 officers; n ties=32,272).
Right: Largest connected component of the co-involvement network (n officers=3,819; n ties=10,712).
[Grey nodes = officer; Blue ties= involved in a common incident together].

Figure 5. Police use of force co-involvement networks, 2012-2016

ERGMs do not perform with missing data as such officers that had missing data on key variables were removed from the network. Before removing these officers, multiple attempts were made to fill in missing values. For example, matching the same officers across all non-missing indicators (see the overview of data, under the section on data, for more context). Overall, 27% of officers and 25% of ties were removed from the largest connected component due to missing data. This led to a final sample of 2,793 officers and 8,059 ties between officers. Table 2 provides a descriptive summary of the component.
Table 2. Officer and Partnership Attributes, New Jersey 2012-2016

<table>
<thead>
<tr>
<th></th>
<th>n</th>
<th>Mean / %</th>
<th>Min, Max</th>
<th>25th</th>
<th>75th</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Officer level</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>2793</td>
<td>92.55</td>
<td>0, 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Race/ Ethnicity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Black</td>
<td>2793</td>
<td>12.10</td>
<td>0, 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td></td>
<td>12.78</td>
<td>0, 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% White</td>
<td></td>
<td>75.12</td>
<td>0, 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Officer experience (tenure), average</td>
<td>2793</td>
<td>8.38 (SD = 6.77)</td>
<td>1, 38</td>
<td>2</td>
<td>13</td>
</tr>
<tr>
<td>Officer experience (tenure), log average</td>
<td>2793</td>
<td>1.68 (SD = 1.05)</td>
<td>0, 3.64</td>
<td>0.69</td>
<td>2.56</td>
</tr>
<tr>
<td>Department moves</td>
<td>2793</td>
<td>1.02</td>
<td>1, 4</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Force Reports, per officer</td>
<td>2793</td>
<td>5.79 (SD = 5.92)</td>
<td>1, 61</td>
<td>2</td>
<td>7</td>
</tr>
<tr>
<td><strong>Network Summary</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total degree centrality</td>
<td>2793</td>
<td>5.77 (SD = 5.11)</td>
<td>0, 42</td>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>Total degree centrality, Stdz.</td>
<td>2793</td>
<td>0.002 (SD = 0.002)</td>
<td>0, 0.015</td>
<td>0.001</td>
<td>0.003</td>
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<tr>
<td><strong>Officer partnerships</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sex</td>
<td>8059</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Male - Male</td>
<td></td>
<td>88.45</td>
<td>0, 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Male - Female</td>
<td></td>
<td>11.07</td>
<td>0, 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Female - Female</td>
<td></td>
<td>0.48</td>
<td>0, 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Race/ Ethnicity</td>
<td>8059</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Black - Black</td>
<td></td>
<td>4.44</td>
<td>0, 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Black - Hispanic</td>
<td></td>
<td>2.57</td>
<td>0, 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Black - White</td>
<td></td>
<td>11.11</td>
<td>0, 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic - Hispanic</td>
<td></td>
<td>3.70</td>
<td>0, 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic - White</td>
<td></td>
<td>15.34</td>
<td>0, 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% White - White</td>
<td></td>
<td>62.85</td>
<td>0, 1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note.  
1 Although the largest connected component does not include isolates, by definition. However, after officers were removed due to missing data, there were 19 isolates in the network. “Isolates” were officers who had used force with a partner with missing data.  
ABBREVIATIONS. Stdz. = Standardized; SD = Standard Deviation.

The component comprises 93% males, with 75% of officers identifying as White, 13% identifying as Hispanic, and 12% identifying as Black. On average, officers had eight years of experience ranging from 1 to 38 years reported on the job across the five years.
Department moves indicate the number of times an officer files a force report in a different department. A value of one would indicate that, across the five years, the officer used force in only one department. In contrast, a value over one would indicate that the officer filed a force report in multiple departments. Officers were unlikely to participate in a use of force incident in multiple departments, with 98% (n=2,734) of officers filing a force report in only one department, 2% (n=57) filing a force report in two departments, and 0.08% (n=2) of officers filing a force report in 3 or more departments across the five years of study.

On average, officers reported six incidents of force ranging from 1 to 61 reports. Figure 6 provides the distribution (top) and cumulative distribution (bottom) of use of force reports for each officer: 19% of officers’ report using force only once, 15% of officers’ report using force twice, 12% of officers’ report using force three times, and cumulatively, 54% of officers’ report using force four or more times across the five years. Notably, approximately one-third (32%) of all officers report using force at a rate above the mean (n=6), whereas 10% of officers account for 35% of all use of force incidents across the five years.
Next, the *degree centrality* measures the number of direct contacts (ties) an officer has. That is, how many different partners an officer has used force with. In this instance, officers, on average, report using force with six other officers (median = 4). Figure 7 provides the distribution (top), and cumulative distribution (bottom) of the number of partners officers use force with. Overall, officers in the largest connected component have
used force with 0 (no partners) to 42 unique partners, with approximately 39% of officers using force with six or more unique partners, and 32% of officers using force with seven or more unique partners across the five years.

Figure 7. Top: Total Degree Centrality for Officers; Bottom: Cumulative Percentage of Officers by Degree Centrality, 2012-2016

At the partnership level, 88% of male officers report using force with another male officer, 11% of partnerships that resulted in force involved a male and female officer pair,
and female partnerships leading to force were generally rare at 0.5%. Finally, turning to race and ethnicity, use of force is most prevalent among pairs of White officers (63%), followed by pairs of Hispanic and White officers (15%), and Black and White officers (11%). By contrast, use of force is less prevalent among pairs of Hispanic officers (4%), Black officers (4%), and pairs of Hispanic and Black officers (3%). The question, thus, driving the analysis, is which attributes (i.e., officer level covariates) and structural network processes drive officers to use force together, beyond chance alone.

**Analytical Strategy**

ERGMs consider a binary relationship - the presence or absence of a tie - as the dependent variable. They are interpretable as the conditional probability of a tie between two actors, given the rest of the network (Hummel et al., 2012; Lusher et al., 2013; Robins et al., 2007; Wasserman & Pattison, 1996). ERGMs are based on the premise that network structure is built through small local network substructures called configurations (also known as structural network configurations) (Hummel et al., 2012; Lubbers & Snijders, 2007; Lusher et al., 2012; Robins et al., 2012). These configurations are conditionally dependent. They generate and self-organize through dyadic relations (i.e., edges) between nodes and represent specific structural patterns unique to the network. They have been applied to understanding race/ethnic homophily in prison (Schaefer et al., 2017), hierarchy and status in a prison unit (see Kreager et al. 2017), trust and multiplexity in a historical case of organized crime in Chicago (Smith & Papachristos, 2016), cohesion in co-offending networks (Malm et al., 2010), gang violence as a function of geographic proximity and group processes (Papachristos et al., 2013), social and spatial proximity in co-offending
ties between neighborhoods (Schaefer, 2011), and criminal collaboration in terrorist networks (Ouellet et al., 2017).

ERGMs are particularly useful as they can disentangle network structure by separating the influence of competing substructure mechanisms that may work simultaneously. In other words, because tie formation can be attributed to multiple processes in the network at the same time, ERGMs draw on whether processes that influence the underlying formation of network structure are due to exogenous effects (e.g., covariate effects), endogenous effects (e.g., network structure), or a combination of both.

Moreover, they can be employed on undirected networks - such that the tie is non-directed - to examine the presence ($X_{ij} = 1$) of a tie between node $i$ and node $j$ and or the absence ($X_{ij} = 0$) of a network tie between node $i$ and node $j$ or on directed networks - such that the direction of the tie matters. By incorporating multiple configurations in the network, many hypothetical structural network configurations can be incorporated into the models to evaluate whether patterns of relations are observed more often than would be expected by chance alone, net of other parameters in the model. These can range from reciprocated ties in weighted directed graphs to various forms of triadic closure and activity effects in undirected graphs. Because co-involvement in use of force tends to be undirected (e.g., officers using force in a common incident), configurations for undirected networks are employed and estimated.

Table 3 represents a summary of structural network (i.e., endogenous network effects) and covariate effects (i.e., exogenous network effects) included in the model. First, the geometrically weighted degree (GWDegree) evaluates whether the probability of connecting to a node depends on their degree. Mostly, it controls for higher degree nodes,
given that models place “high probability on graphs with large degrees” (Snijders et al., 2006, p. 112). If the GWDegree effect is significant and positive, the network is dependent on high-degree nodes. This exhibits a tendency for preferential treatment (Albert & Barabási, 2002), whereby ties are more likely between nodes that are low in degree to nodes that are high in degree compared to ties between nodes low in degree (Snijders et al., 2006).

Second, geometrically weighted edgewise shared partnerships (GWESP) captures transitive and triadic structures in the network (Goodreau, 2007; Hunter, 2007; Hunter et al., 2008; Robins et al., 2007). In most observed networks, triangles are likely to cluster in denser areas of the network. However, in comparison to effects such as “cycle” or “triangles,” which assume that triangles are distributed evenly across the network, GWESP captures the process in which ties between two nodes may “close” multiple triads at the same time, accounting for the number of “triangles” any node may close (Hunter, 2007; Hunter & Handcock, 2006). In other words, rather than providing a simple count of “triangles” a node closes, GWESP provides a “parametric form of the count distribution that gives each additional shared partner a declining positive impact on the probability of two persons forming a tie,” which is more effective in overcoming problems of degeneracy in large networks (Goodreau et al., 2009, pp. 110–111). A significant and positive GWESP effect indicates that adding a tie to a third partner is more likely than chance alone when a given $i$ and $j$ in the network are connected, all else held constant.

Finally, the geometrically weighted dyadwise shared partnerships (GWDSP) considers the probability of adding a tie to a third node regardless of whether a given $i$ and $j$ in the network are connected, all else held constant. While GWDSP measures shared
partners of a dyad \((ij)\), regardless of whether they are connected or not, GWESP measures shared partners for connected dyads \((ij)\). Indeed, when they are added to the model together, GWESP controls for “the distribution of shared partners in connected dyads” “allowing the GWDSP to account for the distribution of shared partner for unconnected dyads” alone (Goodreau, 2007; Harris, 2014, p. 85; Hunter et al., 2008; Snijders, 2002). In contrast, when GWDSP is added to the model without GWESP, estimates may be driven by the distribution of shared partners across connected and unconnected pairs.

The aforementioned structural network configurations are considered simultaneously with exogenous covariate effects across three levels of measurements: node factor represents the main effect of a categorical attribute (i.e., are some types of nodes more likely to form ties with others?); node covariate represents the main effect of a continuous attribute (i.e., are nodes with high levels on a continuous attribute more likely to form ties with others?) and dyadic terms (i.e., are nodes with the same attribute levels more likely to form times with one another?). At the node level, the model considers officer race/ethnicity, sex, experience/tenure, and movement. At the dyadic level, the model considers officer race/ethnicity, sex, county, and department. For example, the probability of using force between nodes that share the same race/ethnicity, sex, or those employed in the same county and department. Finally, for continuous attributes, the model considers the absolute difference in experience/tenure and department moves between partners. For example, the absolute difference in average years of experience between connected dyads \((ij)\) or the absolute difference in the number of moves between connected dyads \((ij)\), a negative coefficient points to stronger homophily, net of all else in the model.
Overall, in models where the parameter is significant and positive – the corresponding configuration is more likely than would be expected by chance alone, net of other parameters in the model; conversely, if the parameter is significant and negative – the corresponding configuration is less likely than would be expected by chance alone, net of other parameters in the model.

Table 3. Network effects for undirected networks

<table>
<thead>
<tr>
<th>Covariate effects (i.e., exogenous effects)</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Node independent attributes</strong></td>
<td></td>
</tr>
<tr>
<td>Race/ethnicity factor</td>
<td>Count of co-involvement, officer by race and ethnicity</td>
</tr>
<tr>
<td>Sex factor</td>
<td>Count of co-involvement, officer by gender</td>
</tr>
<tr>
<td>Experience</td>
<td>Count of co-involvement, officer by years on the force (mean over the five years)</td>
</tr>
<tr>
<td><strong>Dyadic dependent attributes</strong></td>
<td></td>
</tr>
<tr>
<td>Race/ethnicity homophily</td>
<td>Count of co-involvement ties between officers of the same race/ethnicity</td>
</tr>
<tr>
<td>Sex homophily</td>
<td>Count of co-involvement ties between officers of the same gender</td>
</tr>
<tr>
<td>Experience difference</td>
<td>Count of co-involvement ties between officers by difference in their years on the force (mean over the five years)</td>
</tr>
<tr>
<td>County homophily</td>
<td>Count of co-involvement ties between officers from the same county</td>
</tr>
<tr>
<td>Department homophily</td>
<td>Count of co-involvement ties between officers from the same department</td>
</tr>
<tr>
<td>Department moves difference</td>
<td>Count of co-involvement ties between officers by the difference in the number of force reports filed in different departments (i.e., officers moving or working in departments)</td>
</tr>
<tr>
<td><strong>Structural network effects (i.e., endogenous effects)</strong></td>
<td><strong>Structural Configuration</strong></td>
</tr>
<tr>
<td>Node</td>
<td>Officer</td>
</tr>
<tr>
<td>Edge (tie)</td>
<td>Officers involved in use of force together</td>
</tr>
<tr>
<td>GWDegree</td>
<td>Degree distribution in the observed networks (i.e., preferential attachment, activity),</td>
</tr>
<tr>
<td>GWESP</td>
<td>The tendency for officers (who are tied through use of force) to use force with shared partners (i.e., triadic closure, transitivity, clustering),</td>
</tr>
<tr>
<td>GWDSP</td>
<td>The tendency for officers (whether they are tied through a use of force incident or not) to use force with shared partners.</td>
</tr>
</tbody>
</table>
Model specification

ERGMs are similar to generalized linear models (GLMs) and can be interpreted much like a logistic regression. Akin to logistic regressions, estimates can be interpreted in terms of log odds. However, unlike GLMs, which assume independence of observations, ERGMs assume dependence. Namely, it is from the frequency and dependence of local patterns of relations (i.e., ties) that network configurations corresponding to the parameters in the model form and converge. Estimations rely on Markov Chain Monte Carlo (MCMC) maximum likelihood estimation (MLE) simulations of ERGMs, with simulated graph distributions compared with the observed networks (Hunter et al., 2008; Snijders, 2002). For example, ERGMs compare an observed network to all other possible ways the network can be expected to form, allowing us to draw inferences on whether the observed data are consistent with the expected (i.e., sampled) network.

To obtain converged parameter estimates, models are specified in the following ways. First, to reduce model degeneracy, the scale parameter lambda is fit as a curved exponential-family model. The decay from the fixed=false model is used to adjust the alpha (Hunter & Handcock, 2006; Morris et al., 2008). Here, a parameter that is greater than 0 implies a preference for adding edges, and it is useful for sparse networks. Thus, the higher the parameters, the slower the decay. Second, the “MCMC sample size” represents the number of network statistics. The sample is “randomly drawn from a given distribution on the set of all networks, returned by the Metropolis-Hastings algorithm” (2008) (Handcock et al., 2020, p.18). To “increase the precision in the estimates by reducing MCMC error,” sample sizes are set higher for larger networks (Handcock et al., 2020a, p.18). Third, “MCMC intervals” are set to reduce autocorrelation in the sample and reduce the MCMC
error. Like the sample size, the interval is set higher for larger networks (Handcock et al., 2020, p. 18). Fourth, the “MCMC burn-in” represents the “number of proposals to burn before the sample is done” (Handcock et al., 2020, p. 18). The burn-in determines the number of iterations that are necessary before settling on a target distribution (Handcock et al., 2020; Koskinen & Snijders, 2012, p. 145). Fifth, to increase efficiency with larger networks, the models use multiple cores and computing clusters to run the sample (i.e., parallel). Running models with multiple chains also ensures that results are consistent. The MCMC chain is deemed to have converged when it has settled into a pattern centered around a combination of parameter values (Lusher et al., 2013). When models fail to converge, the simulated networks are vastly different from the observed network or that the sampled networks are not from the specified distribution.

Finally, to evaluate model fit, the goodness-of-fit measures are used to compare the observed network parameters with the simulated networks (Hunter et al., 2008). Models were built following Goodreau (2007). The Akaike information criterion (AIC) and Bayesian information criterion (BIC), which provide statistical measures of model fit, are compared across models. Finally, the goodness-of-fit plots comparing observed networks to simulated networks on the best-fitting model are provided. All analyses were conducted in the statnet package for R (http://www.statnetproject.org) (Handcock et al., 2020; R Core Team, 2019).

**Results**

Results are reported in Table 4. Models are estimated in the following sequence. Model 1 is a simple null model with no dependency terms, where ties in the network are assumed

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3 Models 2 to 3 were specified as: MCMC.burnin=100000, MCMC.samplesize=65000; MCMC.interval=65000; parallel=4. Models 4 to 5 were specified as: MCMC.burnin=100000, MCMC.samplesize=85000; MCMC.interval=85000; parallel=4
to form entirely at random. This is the equivalent to a regression model with only an intercept term, where each edge is assumed to be independent of other edges. The second model is the baseline model, integrating covariates effects expected to influence the likelihood of using force with others without any structural network effects. In models, 3-5 structural network effects are gradually added to the model to specify its effects separately. Model 5 is the full model. The BIC of each model is compared to determine any improvement in fit.

The baseline probability of tie formation in Model 1 is significant and negative. This indicates that the probability of tie formation in the network with no dependency terms, where ties are assumed to form completely random, is 0.002. The edge term provided in Model 1 is also equivalent to the network’s overall density, with every tie having about a 0.21% chance of being present. Model 2 evaluates which officer attributes are the most salient dimensions of using force with others. Of the effects considered in Model 2, when all else is held constant, the odds that males, in comparison to females, are more likely to use force with others is 1.30 ($e^{0.26}$). On average, officers with more years on the job are more likely to use force with others than officers who report, on average, fewer years on the job. Officers who move are more likely to use force with others than officers with fewer department moves. The corresponding odds for experience is 1.09 ($e^{0.09}$) and movement is 1.54 ($e^{0.43}$), respectively.

Turning to partnerships, homophily is quite operative for enabling force. For example, in terms of race/ethnicity, homophily is strongest among Black officers, followed by White officers and Hispanic officers. The odds of Black officers using force together

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*ERGM estimates are interpreted in terms of log odds. To obtain the odds, estimates are exponentiated at that value. To obtain probabilities, take the $\exp(a) / (1 + \exp(a))$ of the estimate.*
are 1.90(\(e^{0.64}\)). The odds of White officers using force together are 1.58(\(e^{0.46}\)), and the odds of Hispanic officers using force together are 1.27(\(e^{0.24}\)) compared to mixed-race/ethnicity pairs, holding all else constant. Officers with a similar number of years on the job are likely to use force together than pairs of officers with a greater difference in years of experience (\(e^{-0.39}\)). Lastly, and as expected, officers employed in the same county (\(e^{1.52}\)) and department (\(e^{5.71}\)) are more likely to use force together than those employed in a different county and department.

Table 4. Coefficients and standard errors for ERGMs of the police use of force network

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b (SE)</td>
<td>b (SE)</td>
<td>b (SE)</td>
<td>b (SE)</td>
<td>b (SE)</td>
</tr>
<tr>
<td>Edges</td>
<td>-6.18 (0.01)**</td>
<td>-12.12 (0.37)**</td>
<td>-12.30 (0.37)**</td>
<td>-11.69 (0.38)**</td>
<td>-11.41 (0.36)**</td>
</tr>
<tr>
<td>Match: Black</td>
<td>0.64 (0.10)**</td>
<td>0.64 (0.10)**</td>
<td>0.57 (0.10)**</td>
<td>0.39 (0.09)**</td>
<td></td>
</tr>
<tr>
<td>Match: Hispanic</td>
<td>0.24 (0.10)*</td>
<td>0.22 (0.10)*</td>
<td>0.20 (0.10)*</td>
<td>0.17 (0.09)*</td>
<td></td>
</tr>
<tr>
<td>Match: White</td>
<td>0.46 (0.08)**</td>
<td>0.44 (0.08)**</td>
<td>0.36 (0.09)**</td>
<td>0.30 (0.08)**</td>
<td></td>
</tr>
<tr>
<td>Black (ref: White)</td>
<td>-0.10 (0.08)</td>
<td>-0.10 (0.08)</td>
<td>-0.15 (0.08)*</td>
<td>-0.04 (0.07)</td>
<td></td>
</tr>
<tr>
<td>Hispanic (ref: White)</td>
<td>-0.02 (0.08)</td>
<td>-0.01 (0.08)</td>
<td>-0.09 (0.08)</td>
<td>0.02 (0.07)</td>
<td></td>
</tr>
<tr>
<td>Male (ref: Female)</td>
<td>0.01 (0.09)</td>
<td>0.01 (0.09)</td>
<td>0.00 (0.09)</td>
<td>-0.00 (0.09)</td>
<td></td>
</tr>
<tr>
<td>Abs.diff: Tenure, log</td>
<td>0.26 (0.08)**</td>
<td>0.28 (0.08)**</td>
<td>0.33 (0.08)**</td>
<td>0.20 (0.08)*</td>
<td></td>
</tr>
<tr>
<td>Tenure, log</td>
<td>-0.39 (0.01)**</td>
<td>-0.39 (0.01)**</td>
<td>-0.40 (0.01)**</td>
<td>-0.29 (0.01)**</td>
<td></td>
</tr>
<tr>
<td>Match: County</td>
<td>0.09 (0.01)**</td>
<td>0.08 (0.01)**</td>
<td>0.05 (0.01)**</td>
<td>0.03 (0.01)**</td>
<td></td>
</tr>
<tr>
<td>Match: Dept.</td>
<td>1.52 (0.21)**</td>
<td>1.51 (0.21)**</td>
<td>1.50 (0.21)**</td>
<td>1.45 (0.20)**</td>
<td></td>
</tr>
<tr>
<td>Abs. diff: Dept.</td>
<td>5.71 (0.18)**</td>
<td>5.85 (0.18)**</td>
<td>5.82 (0.18)**</td>
<td>4.09 (0.18)**</td>
<td></td>
</tr>
<tr>
<td>Moves</td>
<td>-0.11 (0.17)</td>
<td>-0.11 (0.17)</td>
<td>-0.14 (0.17)</td>
<td>-0.13 (0.17)</td>
<td></td>
</tr>
<tr>
<td>Dept. Moves</td>
<td>0.43 (0.16)**</td>
<td>0.43 (0.17)*</td>
<td>0.61 (0.17)**</td>
<td>0.40 (0.16)*</td>
<td></td>
</tr>
<tr>
<td>GWDegree, alpha=0.3</td>
<td>1.23 (0.10)**</td>
<td>0.07 (0.11)</td>
<td>1.53 (0.10)**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GWDS, alpha=0.3</td>
<td>-0.06 (0.00)**</td>
<td>-0.07 (0.00)**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GWS, alpha=0.1</td>
<td>2.06 (0.03)**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note.

1 Standard errors (SE) are presented in parentheses.
2 Shaded coefficients are those that remain substantively unchanged in the direction of effect (+/-) and significance (p<0.05) across all models.
3 **p < 0.001; *p < 0.01; +p < 0.05; #p < 0.1

ABBREVIATIONS: Abs.diff = Absolute difference; ref: Reference groups; Dept: Department
In Models 3 to 5, structural network effects GWDegree, GWDSP, and GWESP are gradually added to the model. In Model 3, a positive and significant GWDegree effect ($e^{1.23}$) indicates that the network is centralized on high-degree officers. As such, network structure is likely driven by preferential attachment to officers who use force with many others (i.e., high degree officers) in comparison to those who use less force with other officers (i.e., low degree node). This is not surprising given the skewed nature of the degree distribution (Figure 7). Compared to Model 2, the BIC decreased, signifying that the model fits better than the baseline model with no structural network effects.

In Model 4, a negative and significant GWDSP effect ($e^{-0.06}$) suggests that ties in the network are less likely to be driven by the distribution of shared partners. Indeed, with the addition of GWDSP in Model 4, two effects change: 1) Black officers in comparison to White officers are less likely to use force with others, net of other parameters in the model, though this is marginally significant ($p < .10$), and 2) the odds that Hispanic officers are more likely to use force together reduces slightly in both magnitude and significance. Additionally, the GWDegree effect becomes insignificant. Thus, estimates are driven by the distribution of unconnected or connected shared partners, reducing the likelihood of network centralization. To this end, the BIC continues to decrease, indicating that the model fits better than the previous models. Ultimately, network structure is better explained by incorporating network processes that account for shared partners.

In Model 5, a positive and significant GWESP effect ($e^{2.06}$) reveals the likelihood for officers who have used forced together to have multiple shared partners. By contrast, a negative significant GWDSP effect indicates that officers not linked (i.e., never used force together) are less likely to have shared partners (i.e., use force with the same partners),
indicating fragmentation in the network (Goodreau et al., 2009). As noted previously, when both GWESP and GWDSP are included in the model, GWESP controls for shared partners in connected officer pairs, allowing GWDSP to control for shared partners in unconnected pairs of officers.

Indeed, while several effects are similar in direction and significance to Model 4, there are some discrepancies. When controlling for shared partners at the dyadic and edgewise level, GWDegree is significant in Model 5 (compared to Model 4), indicating network centralization. The marginally significant effect in Model 4, which suggested that Black officers, compared to White officers, are less likely to use force with others, becomes insignificant. Overall, according to the BIC, Model 5 has the best overall model fit.

**Probability of using force by tenure, and race/ethnicity**

The motivation for seeking marginal effects is to determine how a continuous variable influences the dependent variable. In this instance, using the command “edgeprob” from the xergm package can determine the full range of a continuous covariate effect with the probability of tie formation in the network (Brandenberger & Martínez, 2019; Handcock et al., 2020). The goal is to understand the association between tenure (i.e., years of experience) and the probability of tie forming between two officers. In Figure 8, the absolute difference in tenure is on the x-axis, the probability of a tie forming between officers is on the y axis, and each dot represents a potential dyad. Overall, there is a negative correlation - the larger the absolute difference in years of experience between pairs of officers (i.e., heterogenous pairs of officers), the lower the probability of using force together.
Figure 8. **Marginal probability of tie forming by absolute difference in tenure**

Figure 9 disaggregates tenure (i.e., years of experience) and the probability of tie formation by officer race. Here, a pattern is more discernable: relative to pairs of White and Hispanic officers, pairs of Black officers that have been on the job for the same number of years (absolute difference = 0) have the highest probability of using force together. Honing further into these relational patterns, White officers’ probability of using force together generally decreases as differences in tenure increase. By contrast, the probability that pairs of Black officers use force together becomes more stable as differences in tenure increase. Finally, the association between tenure and probability of using force is substantially less distinct for Hispanic officer pairs.
Figure 9. Marginal probability of tie forming by absolute difference in tenure, and race/ethnicity
Goodness of fit

To evaluate the overall fit, Hunter et al. (2008) put forth a goodness-of-fit evaluation technique. The goodness-of-fit compares measures calculated from networks simulated using the fitted model with corresponding measures from the observed network (Lusher et al., 2013). This determines how well the model can reproduce the distribution of various network statistics such as degree, edgewise shared partners, and minimum geodesic distance. These three structural measures are most appropriate, given the undirected nature of the network. A model that demonstrates a good fit is indicated by predicted distributions from the simulated networks centered on the observed network statistics (Lusher et al., 2013).

Figure 10 provides the distributions across the networks simulated using estimates from Model 5 (Table 4). The boxes represent the median and the interquartile range; the grey lines represent 95% confidence intervals. The black line represents the degree, edgewise shared partners, and minimum geodesic distance distribution for the observed network, respectively. Overall, except for the geodesic distances, in which the simulated model overestimates from six to 13 and underestimates from a distance of fifteen or more, the model-fit for degree and edgewise shared partners look reasonably well. With degree, the observed statistics fall within the range of the simulated values, with p-values that indicate no significant differences between the simulated and observed network. With edgewise shared partners, the simulated model overestimates the number of edges with one and two shared partners and underestimates the number with four or more; the p-values indicate no significant differences between the simulated and observed networks.
Discussion

While use of force is relatively rare, the perception that force is a suitable mechanism of conflict management and thus is used more than is necessary has implications for community wellbeing and cohesion (Desmond et al., 2016), civilian’s perceptions of procedural justice, and police legitimacy (Gau & Brunson, 2010; Tyler & Huo, 2002; Weitzer, 2002; Westley, 1970) and long term psychological and health consequences in communities experiencing abuses (Bor et al., 2018; Edwards et al., 2019; Legewie & Fagan, 2019; Soss & Weaver, 2017). Exponential random graph family models have been used to understand the source of tie formation in prison, drug networks, gang violence, misconduct networks, and terrorist networks as we all as others. In the current study, a similar approach was taken to examine the likelihood of officers using force together, thus

Figure 10. Goodness-of-fit diagnostics, Model 5
disentangling the “shared aspect” of police work (Bittner, 1970; Manning, 1977; Muir, 1967; Skolnick, 1966).

The study finds that police use of force tends to be a grouped phenomenon likely to be concentrated on a subset of officers. Broadly, results can be categorized into four main findings. First, police use of force is not evenly distributed but concentrated on a small number of officers that drive network connectivity. This finding is consistent with prior research, which overwhelmingly finds that most crime and violence is concentrated, and unevenly distributed in select homogenous populations and geographical spaces (Braga et al., 2010; Papachristos & Bastomski, 2018; Sherman et al., 1989; Weisburd, 2015; Wolfgang et al., 1972). For example, in a cross-city comparison of crime concentration, Weisburd (2015) found that 25% of the crime is found between 0.8% and 1.6% of the street segments across five cities. Relatedly, other studies have found the crime concentrates in select “at-risk” populations. Criminological theories such as social learning and opportunity theories argue that crime and delinquency occur within the context of delinquent peers (Akers, 1985; Haynie, 2001) with 25% to over 50% of all offending events involving a co-offender (Carrington, 2009; Felson, 2003; McGloin & Piquero, 2010).

Perhaps one of the most salient observations in this line of work is that the network of one’s peers’ group can amplify (or reduce) the processes that promote crime and delinquent behaviors (Akers, 1985; Short & Strodtbeck, 1965; Tremblay, 1993).

This study finds that police violence operates in much of the same way. Of the 17,845 officers who used force in New Jersey from 2012 to 2016, 81% of officers used force alongside one or more of their colleagues, and 62% of officers used force alongside two or more of their colleagues. These local patterns of force weave together to form a larger
network structure. For example, the largest connected component of the use of force network, where there is no missing data on officers, and every officer has participated in force with at least one other officer, comprises roughly 16% of officers who have reported using force, and one-quarter of force reports in New Jersey over the five years. Second, levels of force within the largest connected component are highly skewed and centralized. On average, officers report 5.79 use of force incidents over the five years; however, 10% of officers, who report the most force in the largest connected component, account for 35% of all force incidents across the five years.

Moreover, roughly 39% of the officer’s report using force with six or more unique partners, whereas the top 1% of officers use force with 25 or more unique partners. Coupled together, the skewed nature of the degree distribution and the centralized nature of the network on high-degree officers indicates that a subset of officers is likely responsible for much of the observed connectivity in the use of force network. These findings appear to confirm the “networked” nature of police behaviors, demonstrated in studies by Wood, Roithmayr, and Papachristos (2019), who find that complaints of misconduct were concentrated on a small number of officers, as well as Ouellet et al. (2019) and Quispe-Torreblanca and Stewart (2019), who find that the composition of an officers’ network and exposure to deviant colleagues increases an officers’ likelihood of misconduct.

Third, there is significant variation in officers’ social similarity and the likelihood of using force with peers. Findings reveal that male officers were more likely to use force with others in comparison to female officers. These findings may be suggestive of the diffidence of female officers to demonstrate aggressive behaviors such as displaying coercive activity, making arrests, and issuing tickets (see Bloch & Anderson, 1974; Grant,
2000; Hale, 1992; Herbert, 2001; Lonsway, 2001; Paoline & Terrill, 2005) and, thus, having fewer opportunities to resort to force with others. For example, while New Jersey’s 2017 Diversion and Inclusion Annual Report indicates that roughly 35% of officers employed in New Jersey are female (Office of the Attorney General, 2017), only 7% of females in the current study report using force with others. Females may be inclined to report fewer instances of force overall, thus partaking in fewer instances of force with colleagues.

Next, on average, officers with more years on the job were more likely to use force with others than officers that report, on average, fewer years on the job. This finding is in stark contrast to prior studies that have found that younger and less experienced officers are more likely to engage in force. More experienced officers tend to be assigned to patrol duties or placed in administrative or managerial roles that reduce their exposure to the public (Aamodt, 2004; Cohen & Chaiken, 1972; Garner et al., 2002; McElvain & Kposowa, 2004), whereas younger officers are generally more active (Brandl et al., 2001, p. 523; Worden, 1989). However, when considering use of force with a colleague, officer experience, as indicated by the number of years on the job, may substantially influence an officers’ probability of being tied to other officers in the network. Indeed, a positive association could be due to greater exposure to other officers’ overtime.

Fourth, use of force tends to concentrate on select partnerships. First, turning to race/ethnicity: pairs of Black officers, White officers, and Hispanic officers were more likely to use force together than a racially heterogeneous officer pair. This could be due to the contextual nature of these ties. For example, officers who share traits may be members of a common group, ultimately impacting how they behave together. For example, work
on subgroup formation has consistently found race/ethnicity to be one of its most robust defining features of group formation – with race/ethnicity found to be one of the strongest predictors of friendships in schools (Moody, 2001), friendship and power attribution in prisons (Kreager et al., 2017; Schaefer et al., 2017), cooperation in the workplace (Mollica et al., 2003), and more broadly, a way of determining trust (Gambetta, 2011; Young & Haynie, 2020). Indeed, it may be the case that officers who share in the same race/ethnicity are likely to share in elevated levels of trust with one another (McPherson et al., 2001), and thus, likely to serve as “trustworthy accomplices” (Schaefer et al., 2014) or “suitable offenders” (Tremblay, 1993). Trust is a vital facet of policing – it not only allows officers to predict behaviors and to develop a set of expectations about those behaviors, but it also provides officers the opportunity to learn about others and to gauge one another’s dependability. As a result, officers from a common racial/ethnic group may be more inclined to engage in force, or even in misconduct, together (Wood et al., 2019) because they trust and rely on each other’s behaviors (i.e., having each other’s backs), and these relations may ultimately be deemed less risky (McCarthy et al., 1998).

Relatedly, a host of studies have argued that Black or Hispanic officers may be better equipped to de-escalate police-civilian encounters and reduce tensions between minorities and the police due to shared cultural experiences (Decker & Smith, 1980; also see Kelly & Farber, 1974; Kelly & West, 1973; Leinen, 1985; Walker, 1983). It may be the case that pairs of Black or Hispanic officers are disproportionately assigned to neighborhoods with higher crime rates, placing officers in situations that may require force more so than in other areas (Alex, 1969; Fyfe, 1988; Smith, 1986; Walker et al., 1972). To this end, mixing officers (e.g., White and Black officers or Hispanic and Black officers,
etc.) may continue to reduce the social distance between communities and police and racial tensions by mitigating the stereotype of having all White officers or all Black officers on the scene of an event (Levin & Thomas, 1997). Moreover, it may also act as a deterrent for officers, reducing the opportunity (or the comfort) that select officers have to use force together.

Lastly, pairs of officers with a similar number of years on the job were more likely to use force together. By contrast, pairs of officers who varied in their reported number of years on the job were less likely to use force together. This could be because officers with more experience benefit from continued and repetitive exposure to various situations. Ultimately, their accumulated exposure may positively impact how their partners, who may be less experienced, are socialized to deal with civilians and manage their encounters with the public (Bayley & Bittner, 1984; Bayley & Garofalo, 1989; Riksheim & Chermak, 1993). More experienced officers may also alleviate some of the in-experiences or tendencies of new or younger officers (Skolnick, 1966; Van Maanen, 1974), reducing the likelihood of both conflict and misconduct over time (Wood et al., 2019).

**Key Challenges and Implications**

Capturing use of force behaviors through officer partnerships is a useful first step in understanding larger relational processes; however, it does come with several challenges. First, the current study focuses on a subset of force incidents. ERGMs are employed on the largest connected component of the use of force network, thereby providing an overview of force across 10% of departments, covering 71% of New Jersey counties. Selecting to work on the largest connected component is a common methodological approach, especially when evaluating larger networks as they require a considerable amount of
computing power and time to run an MCMC simulation (Hummel et al., 2012; Shumate & Palazzolo, 2010). Results may differ if networks are delineated based on common departments or counties and compared with one another. In this instance, network boundaries would vary, altering the component's size (or unit of measurement) and the subset of officers in the network. Second, ERGMs rely on cross-sectional data, which does not capture complex temporal dependencies and time. By contrast, Temporal ERGMs do not require a linear change in network structure over time. As such, it can account for change in officer relations (Leifeld et al., 2015). However, given how sparse the network is and the fact that we are interested in officers ever having used force with a colleague, delineating networks into time frames would substantially reduce the size of the network and impede parameter estimates and model convergence.

Third, because these are self-reports, the quality and quantity of data depend on the reporting officer completing the use of force report in a consistent, thorough, and accurate manner. Relatedly, specific features of the organization and department impact reporting behaviors leading officers to over-report if their department employs specific policies (i.e., force reports as a measure of crime control policies, gauge the effectiveness of the policy, or uses data for other means such as promotions), underreport or not report at all (e.g., to avoid demotions, discipline, or paperwork), relative to officers employed in other agencies (Alpert & MacDonald, 2001; Garner et al., 2002; Hickman et al., 2008; Terrill & Mastrofski, 2002). Data that are missing or inaccurate pose specific challenges as it reduces the sample’s size and quality (Rubin, 1976). Regardless of the various missing data patterns, they may lead to selection bias by impacting the reproducibility and robustness of
findings with the overrepresentation or underrepresentation of specific groups or individuals.

For data that does not have the full set of relations, which may be conceivable with self-reports, sampling techniques such as snowball sampling, and alter-driven surveys have been used to capture the full representation of the network (Heckathorn, 1997; Salganik & Heckathorn, 2004). Others have modeled missing data by using a maximum likelihood estimator to generate the complete network (Handcock & Gile, 2007). However, given that omissions may not have been at random, it prevented missing data analysis on ties. Likewise, officers may be missing attribute data (i.e., sex, experience, race/ethnicity). To this end, officers were matched across all non-missing indicators to reduce the effects of missing data. Despite these limitations, official force reports are consistently the most efficient source for gathering large amounts of data, especially across multiple departments (Terrill, 2001). Self-reports are gathered to be objective assessments of the situation. They undergo an extensive review process that is verified and substantiated by supervisors. Finally, focusing on a single state raises issues of generalizability. Results are limited to officers’ uses of force in New Jersey and the laws to report force by the Attorney General. Provided that there is no standard practice for defining and measuring use of force across the country, results may not be comparable to force incidents in areas outside of New Jersey. Nonetheless, this is an important first step in understanding larger trends at the state level and patterns of force behaviors.

This study has important implications by drawing on larger systematic patterns of police use of force. Studies invoke police culture as occurring within cohesive groups, marked by group solidarity and ‘brotherhoods’ (Brown, 1988; Manning, 1977; Muir, 1967;
Skolnick, 1966; Westley, 1970). While police culture itself may not promote abuses, it is the “shared aspect” of police work that cultivates interdependencies among officers. In return, these interdependencies shape how officers understand and select into their role, how they socialize into police culture, and how they learn to neutralize and justify their behaviors and that of their peers (Chappell & Piquero, 2004; Manning, 1977; Muir, 1967; Skolnick, 1966; Westley, 1970).

Traditionally, police use of force has often been restricted to officer-level, departmental-level, and situational-level characteristics, without much consideration given to officers’ social similarities and dependencies in selecting to use force together. Expanding our understanding of police use of force by paying attention to larger network dependencies reflects the realities of police work. For starters, it extends our understanding of patterns of police behaviors, which are influenced by larger occupational and organizational contexts, and emphasizes relational processes that are central to understanding delinquent behavior, including social learning and opportunity perspectives (Akers, 1985; Wilcox & Cullen, 2018). Likewise, by understanding how these events systemically concentrate through networks, we can understand relational properties such as the diffusion of behaviors, the diffusion of violence across police departments, and an officers’ “reach” regarding whom they use force with and how often. Within these larger networks, individuals learn and are afforded the opportunity to engage in normative or violent but socially acceptable behaviors (Agnew, 1991; Akers, 1985; Haynie, 2001).

Findings also provide important avenues for intervention strategies that enhance officer safety while potentially preventing future instances of officer misconduct and excessive force incidents. This is to say that it matters if some officers are more coercive
than others. These officers may be displaying patterns of behaviors that may contribute to
the emergence or diffusion of problematic behaviors overtime. By paying greater attention
to the intricacies of the job and the structural makeup of the department, we may be able
to provide preventive measures that start at the top (i.e., hiring practices, leadership roles,
promotions, and demotions) and weave into an actionable plan (i.e., assignment of officers
in specialized units or geographical spaces, training provisions).

From an applied stance, for example, when supervisors or upper management are
tasked with assigning officers to workgroups or their partners, they may do so in a problem-
oriented, informative, and data-driven way (Goff & Barsamian, 2012). There is evidence
that pairs of officers that are less alike, demographically, are less likely to use force
together. However, when it comes to race and ethnicity, diversifying through hiring
practices, on its own, might not be that effective if officer workgroups continue to exhibit
this tendency towards homophily (Levin & Thomas, 1997). Instead, it may be more critical
that minority officers are integrated into the agency and given the opportunity to work
alongside their White peers.

Likewise, the idea of continuing to partner less experienced partner officers with
more experienced officers might prove useful for de-escalating potentially violent
situations and socializing prospects and recruits into the police culture (Skolnick, 1966;
Van Maanen, 1974). As noted previously, those with greater experience might have the
benefits of continued and repetitive exposure to various situations over time, including use
of force events. This exposure may positively impact how officers manage conflict in their
encounters with the public and how they mentor officers less senior to them to deal with
civilians on a day-to-day basis. Finally, by applying a networked approach to police
behaviors, departments may allot intervention and training provisions on a subset of well-connected high-risk officers that are likely to resort to force or those who consistently fail to adopt an appropriate, nonviolent, exit strategy (Alpert & Walker, 2000; Walker, 2001; Walker et al., 2001). This tactic may not only promote change in officer behaviors, at the individual level, but also build accountability among a broader set of officers.
STUDY 2. SPECIALIZATION AND VERSATILITY OF FORCE

Reexamining the fatal incident involving George Floyd in Minneapolis, the Minneapolis Police Department (MPD) is the largest police department in Minnesota. Yet, the department is rooted in a deep history of accusations of police abuse and disproportionate use of force (Oppel & Gamio, 2020). From 2006 to 2012, they had 14 million in payouts for alleged police misconduct (Furst, 2013). Specifically, of the 439 complaints filed against Minneapolis officers, none of the officers were reprimanded or disciplined for any wrongdoing (Furst, 2013). Since then, only 1 percent of complaints against police officers were adjudicated (Furber, Eligon & Burch, 2020). It was widespread calls for police reform following George Floyd’s death that finally led the MPD to overhaul its use of force policy (Lauritsen, 2020). However, the question remains: are widespread patterns of coercive behaviors unique to the department and its organizational and structural composition, or can it be attributed to the city's ecological makeup (i.e., the department's jurisdiction).

Police officers’ occupational and organizational behaviors are shaped by a working environment that emphasizes a culture of uncertainty, danger, efficiency, and use of coercive power (Skolnick, 1966; Westley, 1970). However, how officers adapt to, learn, and neutralize occupational and organizational attributed stressors is not uniform. On the one hand, scholars have argued that officers adhere to a police culture that enforces a single way of dealing with the police role. For example, Crank (1998) asserted that “street cops everywhere tend to share a common culture because they respond to similar audiences everywhere” (p.26). Indeed, this is because officers are exposed to similar populations (Crank, 1998; Moon & Zager, 2007), and thus share similar beliefs about civilians (Manning, 1977; Rubinstein, 1993), aggressive and coercive policing strategies (Bittner,
1970; Brown, 1988; Van Maanen, 1974; Worden, 1995), the police role and enforcement of the law (Bittner, 1970; Brooks et al., 1994; Sun, 2003), and types of bureaucracies and supervision (Crank, 1998; Paoline, 2003). These views are transmitted between officers and transcend across time and place. Thus, in line with this perspective, it has been proposed that variations between officers such as their sex, race/ethnicity, age, education, and the situations encountered tend not to be related to their behaviors (Adams et al., 1999; Geller & Toch, 1995; Riksheim & Chermak, 1993).

On the other hand, it has been argued that variations in the structure, size, and composition of departments introduce heterogeneity across working environments (Hickman & Piquero, 2009; Ingram et al., 2013, 2018; Terrill & Paoline, 2017). Though occupational and organizational attitudes are shared through officers’ interactions and exposure to common features in their working environments, heterogeneous and dynamic factors between departments influence officer behaviors, attitudes, and overall interactions with civilians (Terrill et al., 2003). In one of the first studies focusing on organizational and agency styles across jurisdictions, Wilson (1968) distinguished police agencies by their administrative and professionalism levels. He argued that efforts at the organizational and departmental level influence how police exercise coercive authority. Similarly, Eitle et al. (2014) and others focused on how features of the department, such as its size, influence police behaviors (see also, Huff, White & Decker, 2018). Because policing in America is largely decentralized, these studies highlight that some aspect of the police agencies, such as its social structure (Klinger, 1997; Skolnick, 1966; Wood, 2017), composition (Cao et al., 2000; Paoline & Terrill, 2007; Parker et al., 2005), administrative features and policy (Hickman & Piquero, 2009; Terrill & Paoline, 2017; White, 2001), and standards in hiring
practices (Parker et al., 2005) determine with how officers display their use of coercive authority. Along these lines, Klinger (1997, 2004) and others (see Mastrofski et al., 2002; Smith, 1986; Terrill & Reisig, 2003) have also suggested that factors related to the environment influence the deployment of police services and police behaviors. Specifically, Klinger’s (1997) ecological theory of police responsiveness has suggested that residents of disadvantaged communities with high levels of crime have unparalleled experiences with the use of physical and aggressive officer behaviors (see also Jacobs & O’Brien, 1998), slower response times, and are privy to fewer police services (see also Anderson, 1990).

The current study expands on this linkage by evaluating police use of force at the department level. It adopts a criminal career paradigm to indicate whether officers specialize in using force within a shared working environment (i.e., department groups) and whether differential environmental patterns and composition of police departments are associated with patterns of force (Bursik et al., 1990; Klinger, 1997, 2004). Research examining groups as the unit of analysis has added to our understanding of peer influences and crime (Warr, 2002), trajectories in offending behaviors (Van Koppen et al., 2010), and conflict and collaborations in organizations (Gould, 1993; Sellin, 1938). The current study follows a similar approach by treating police departments as the unit of analysis, thereby treating force as a collective feature of the department. Additionally, it follows calls to shift from measuring police use of force as a dichotomous variable (Garner et al., 2002; Lawton, 2007; Smith, 2008; Terrill & Paoline, 2017) and instead focuses on variations in types of force (i.e., constructive, physical, mechanical, deadly) to understand force usage in departments.
The aim of the current study is two-fold. Through an individualized measure of diversity (i.e., diversity index), the first aim is to examine whether officers exposed to similar social and environmental contexts in a shared department show specialization or diversity in their use of force behaviors. The second aim is to examine whether variations in the organizational characteristics of police departments and environmental determinates help to sustain use of force patterns. This approach captures how patterns of force persist and vary across environmental space and occupational and organizational culture (Klinger, 1997, 2004).

**Understanding officer use of force at the organizational and environmental level**

Criminology perspectives have long argued for the salience of the group for understanding the prevalence and adoption of offending behaviors. It follows that how individuals adopt behaviors and understand information are influenced by the social, structural, and environmental context (Lewin, 1948). Indeed, how officers come to understand and espouse their working environment, followed by occupational norms, values, and avenues of neutralization, can substantially impact the degree and frequency of inappropriate and aggressive behaviors, excessive use of force, and misconduct (Barker, 1977; Bliese et al., 2002; Chappell & Piquero, 2004; Hunt & Manning, 1991; Waegel, 1984; Worden, 1995).

For example, Ingram, Paoline, and Terrill (2013) and Ingram, Terrill, and Paoline (2018) suggest that police behaviors and attitudes be examined under the umbrella of collective efficacy (Sampson et al., 1997) and street culture (Berg et al., 2012) with shared attitudes and behaviors prescribed to be a collective feature of the occupational environment. Under this perspective, the officer workgroup provides an immediate and proximal environment for how broader social and cultural features important to an officers’
day-day role develop and persist. For example, Ingram, Terrill, and Paoline (2018) looked at the extent to which workgroup culture and strength were associated with officers’ use-of-force behaviors. Among three cultural attitudes central to the organizational and occupational elements of police work, they found that workgroups that valued aggressive patrol tactics were likely to use force, do so more frequently, and to higher degrees, than workgroups that placed less value on aggressive patrol tactics. Echoing previous findings by McCluskey, Terrill, and Paoline (2005) and Terrill, Paoline, and Manning (2003), the authors concluded “that officers who work in environments that subscribe to a culture of aggressive patrol practices or punitive management perceptions behaved similarly” (p. 801).

Mastrofski (2004), however, moved away from a cultural framework and emphasized the function and structure of police departments. Specifically, he argued that police departments, like other formal organizations, seek to “establish structures (centralization, hierarchy, rules), incentives and sanctions, supervision, and so on to coordinate and control the activities of the organization’s members” (Mastrofski, 2004, p. 103). A long line of research has linked departmental structure with coercive use of force, focusing on the association between various characteristics of departments (Alpert & MacDonald, 2001; Wilson, 1968), such as department size, administrative policies (Shjarback & White, 2016; Terrill & Paoline, 2017), diversity (Walker, 2004), and police use of force. Essential to this perspective is that agencies with different organizational rules, guidelines, and structures will also differ in aggregate rates of force.

Focusing on administrative policy, professionalism, and use of force, Shjarback and White (2016) found a negative association between an agency's commitment to college
education and violence levels in police-civilian encounters. Under this framework, more educated police forces should be more professional and less likely to engage in unwanted behaviors. Other studies have highlighted the importance of diversifying the police force to improve police and community relations (Walker, 2014). For example, police departments that demonstrate a commitment to equal opportunity and diversity in the workplace by employing a higher proportion of females and minority officers are more likely to maintain legitimacy and have healthier police-community relations (Schuck, 2014; Schuck & Rabe-Hemp, 2016). Indeed, reducing the social distance between police officers and civilians is believed to reduce aggressive and punitive crime control strategies (Smith & Holmes, 2014; Walker & Archbold, 2018).

Lastly, turning to environmental determinates, studies (see Klinger, 1997, 2004; Mastrofski et al., 2002; Terrill & Reisig, 2003) have stressed a link between environmental context and police use of force. For example, Klinger’s (1997) ecological theory of police responsiveness maintains that formal police efforts are dependent on the neighborhood's social and economic characteristics. Following Klinger's (1997) perspective, the type and severity of police force and other police practices will vary in accordance with the neighborhood where police encounter suspects. Relatedly, earlier works by Bayley and Mendelsohn (1968) and Smith (1986) both argued that suspects encountered in disadvantaged and high-crime neighborhoods are likely to be perceived by officers with greater suspicion, thereby increasing the probability that the suspect will encounter more aggressive and coercive policing behaviors, irrespective of the suspect's characteristics or behaviors (see also Terrill & Reisig, 2003).
As demonstrated above, a review of relevant research has identified several variables at the organizational and environmental levels that significantly influence police use of force. The current study leans on these findings by including relevant measures capturing organizational characteristics and environmental determinates of departments to understand larger patterns of force (i.e., specialization and versatility) across police departments in New Jersey.

**Specialization and versatility of force**

Understanding “collective force” at the department level is guided by the criminal career paradigm, which has traditionally characterized individuals’ offending patterns over their “criminal career” (Blumstein et al., 1988; Blumstein & Cohen, 1987). By moving away from individual behavioral patterns to group-level patterns, within-individual variations are contextualized within the context of the individual's (or group's) overall trajectory. This framework provides a “birds-eye view” of departments’ overall composition, helping to understand the social and environmental context in which officers are embedded (Lewin, 1948).

Recall from research on criminal careers; offending can be highly specialized, with criminal behavior consisting of only one type of offense, or offending can be highly versatile, with criminal behavior consisting of many offenses over an extended period of time (Blumstein et al., 1988; Paternoster et al., 1998). Like specialization and versatility at the individual-level, groups specialize and dabble in different types of offending behaviors. For example, terms such as “criminal networks,” “corporate crime,” “group crime,” “organized crime,” “gang networks,” and “terrorist networks” are described as a collection of offenders that collaborate in varying degrees, combinations, and capacities (Block,
1979; Bruinsma & Bernasco, 2004; Malm et al. 2010; Morselli, 2010; Morselli & Tremblay, 2004; Ouellet et al., 2017; Papachristos et al., 2013; Sarnecki, 2001). These groups require a specific form of collaboration and organization. Their developmental trajectories are primarily interdependent, formed, and shaped by others' behaviors and actions within their immediate network.

In police departments, specialization and versatility in force might not only be a function of patrol work and the opportunity to use force but signal a cultural learning environment that is fundamental for understanding officer behaviors (Crank, 1998; Ingram et al., 2013; Paoline, 2003; Skolnick, 1966). Namely, departments serve as important structural boundaries that shape and constrain officer behavior (Ingram et al., 2013; Klinger, 1997; Skolnick, 1966). Within these departments, officers interact and share in formal and informal activities that help them build a sense of collective identity (Bennett, 1984; Klinger, 1997; Rubinstein, 1993; Skolnick, 1966). Because officers share in the same occupational and organizational working environments, they are exposed to similar stimuli and stressors and thus depend on one another to navigate their day-to-day roles. These relationships influence patrol decisions, serving as conduits for how officers learn and are trained to use certain types and levels of force (more severe vs. less severe) in their encounters with civilians, as well as how these behaviors are rationalized and neutralized on the job (Barker, 1977; Bliese et al., 2002; Hunt & Manning, 1991; Ingram et al., 2013, 2018; McCluskey et al., 2005; Sykes & Matza, 1957).

As such, exploring this question of specialization and versatility in use of force patterns at the workgroup level provides the opportunity to measure heterogeneity and homogeneity within and between departments. Under this perspective, the department
signals an immediate (i.e., local) and proximal (i.e., peripheral) appreciation for how broader social, organizational, and temporal variations translate to officer interactions with civilians. Because officers are immersed in the same environment, they are likely to share the same level of social deviance compared to officers in other departments (Klinger, 1997). Thus, using departments at the unit of analysis, this study follows calls by Klinger (1997, 2004) to understand patterns in how departments exercise their use of coercive authority across different environmental and organizational contexts. The aim of the study is two-fold: 1) examine whether officers in the same department are likely to use similar types of force, such that levels of force cluster (i.e., specialize in force); and 2) examine whether there is an association between the characteristics of police departments and specialization (or versatility) of force.

**Data and Methods**

To capture group-level measures, officers were collapsed into the department for which they file a force report from 2012 to 2016. For officers who filed a force report in more than one department, they were included in the department they filed the most reports (modal category). Departments are an ideal unit of analysis. They represent distinct departments where collective behavior and group norms are most salient and remain relatively stable over time (Klinger, 1997). Simultaneously, departments in New Jersey operate under similar use of force policies, providing a baseline for understanding specialization and versatility in patterns of force.

Figure 11 (on the left) shows the use of force co-involvement network at the officer level. The node’s color represents the officer’s department. As expected, officers in the same department who have used force together tend to cluster together. Figure 11 (on the
right) is the use of force co-involvement network at the group-level. Compared to the figure on the left, this representation goes from the individual to the group level. Each polygon represents 1 unit of analysis (i.e., one department) (n=458). Appendix 7 describes how measures were aggregated at the group-level, providing definitions and the data source for key variables.

**Figure 11. Police use of force co-involvement networks (n = 12,659) by department, 2012-2016**

**Data sources**

Data on the prevalence of officer use of force (i.e., the volume of force, per department) and type of force were obtained from the Force Report. In contrast, New Jersey municipal offense and demographic data were obtained from two sources: the New Jersey Uniform Crime Reporting System (Office of the Attorney General, 2012-2016) and the Law

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1 Data on the population, crime rate, and whether the municipality is considered Rural, Suburban or Urban from 2012 to 2016 were obtained from [https://www.njpp.org/ucr/uniform-crime-reports.shtml](https://www.njpp.org/ucr/uniform-crime-reports.shtml). These reports are based on crime statistics submitted to the New Jersey Uniform Crime Reporting System by every New Jersey law enforcement agency for the year 2012 to 2016.
Enforcement Management and Administrative Statistics (LEMAS) (United States Department of Justice, 2015).8

*New Jersey Crime Reports.* Data on the estimated population, crime rate, and the characteristic of the municipality (i.e., rural, suburban, urban) and police employee data (i.e., the total number of full-time sworn officers by sex/gender) for each municipal police department were obtained from the NJ Crime Reports. As part of the Uniform Crime Reporting Crime Program, all law enforcement agencies in New Jersey must submit monthly and annual summary crime reports to the New Jersey State Police. The New Jersey State Police, as authorized by the Attorney General, is responsible for collecting, combining, and submitting the crime data received to New Jersey Uniform Crime Reporting System. While the state is geographically composed of 21 counties containing 565 incorporated municipalities, use of force data from the Force Report were matched for 461 municipal police departments. The New Jersey State Police and two departments were deleted due to missing data on key variables leading to a final subsample of 458 departments.

*Law Enforcement Management and Administrative Statistics (LEMAS).* Data on the racial/ethnic composition of officers employed in each department and education requirements for each municipal police department were obtained from LEMAS. LEMAS is a self-report survey that collects data from a nationally representative sample of state and local law enforcement agencies in the United States. Survey questionnaires are sent to general-state and local law enforcement agencies such as local police departments, sheriffs’

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offices, and the 50 primary state law enforcement agencies. The survey is mailed out to agencies that employ 100 or sworn personnel, with smaller agencies sampled from strata based on the number of officers employed. Overall, LEMAS provided data on a subset of 122 law enforcement agencies in the state of New Jersey. Of the 122 law enforcement agencies, the New Jersey State Police and sheriff’s offices, not reported in the Force Reports, were excluded from the analysis leading to a final sample of 114 departments.

**Overview of the departments**

Table 5 provides a summary of the composition of the departments. The number of officers employed across departments from 2012 to 2016 ranged from three to 1046 officers, with, on average, 43 officers employed in each department (SD = 75.59). In terms of force, departments were, on average, filing about 138 (SD = 291.91) across the five years.

Relative to the number of officers employed in each department – departments were predominately male (95%). Of the officers employed across the 114 departments, 80% were identified as White, 10% were identified as Hispanic, 7% as Black, and 2% of officers identified as “Other.” Likewise, 79% of departments required that new sworn officers have a high school diploma or equivalent, 14% of departments required an associate degree or equivalent, and 7% required some college education or a bachelor’s degree or equivalent.9

In each force report, the officer has to provide the “subject force nature,” indicating the nature of the force used on the subject (see Appendix 7). The nature of reported force in each use of force report was categorized into one of the four types: constructive force, physical force; mechanical force; and deadly force as defined by the Attorney General’s Use of Force Policy (2000; 1985) (see Appendix 1). If an officer resorted to using more

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9 Only 1 department collapsed into this category reported no minimum education requirement.
than one type of force in a single incident, the highest level of force was measured. The most common type of force reported, on average, was physical force (89%), followed by mechanical force (9%), constructive force (1%), and deadly force (1%) per department.

Finally, prior research has indicated that force varies across ecological space (Hickman & Piquero, 2009; Klinger, 1997; Terrill & Reisig, 2003), as such municipal-level data such as the estimated population, crime rate, and the residential characteristic of the area that each department serves were collected. On average, departments served an area with an estimated population of 18,624 (SD = 25,771) civilians, where the mean crime rate was 19 per 1000 persons (SD = 17.77). Mean crime rates across municipalities range, however, from 1.66 to 152 per 1000 persons. Most departments police in the suburbs (50%), followed by urban areas (33%) and rural areas (16%).
Table 5. Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>n</th>
<th>Mean / %</th>
<th>Std. Dev.</th>
<th>Min, Max</th>
<th>25th</th>
<th>75th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size (i.e., number of officers employed)</td>
<td>458</td>
<td>42.48</td>
<td>75.59</td>
<td>3, 1046</td>
<td>14</td>
<td>45</td>
</tr>
<tr>
<td>Volume of force (i.e., number of Force Reports)</td>
<td>458</td>
<td>138.74</td>
<td>291.91</td>
<td>3, 2842</td>
<td>19</td>
<td>128</td>
</tr>
<tr>
<td>Sex</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>458</td>
<td>0.95</td>
<td>0.046</td>
<td>0, 74.1</td>
<td>0.93</td>
<td>1</td>
</tr>
<tr>
<td>Female</td>
<td>458</td>
<td>0.05</td>
<td>0.046</td>
<td>0, 0.26</td>
<td>0.02</td>
<td>0.07</td>
</tr>
<tr>
<td>Race/ Ethnicity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>114</td>
<td>0.80</td>
<td>0.22</td>
<td>0.06, 1</td>
<td>0.71</td>
<td>0.96</td>
</tr>
<tr>
<td>Black</td>
<td>114</td>
<td>0.08</td>
<td>0.15</td>
<td>0, 0.95</td>
<td>0.0</td>
<td>0.08</td>
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<tr>
<td>Hispanic</td>
<td>114</td>
<td>0.10</td>
<td>0.14</td>
<td>0, 0.57</td>
<td>0.01</td>
<td>0.14</td>
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<tr>
<td>Other</td>
<td>114</td>
<td>0.02</td>
<td>0.03</td>
<td>0, 0.21</td>
<td>0.0</td>
<td>0.03</td>
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<tr>
<td>Education Requirements</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High school(^1)</td>
<td>114</td>
<td>0.79</td>
<td>0.41</td>
<td>0, 1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Associate degree</td>
<td>114</td>
<td>0.14</td>
<td>0.35</td>
<td>0, 1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>College/Bachelor's Degree</td>
<td>114</td>
<td>0.07</td>
<td>0.26</td>
<td>0, 1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Use of force type (^2)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constructive force</td>
<td>458</td>
<td>0.01</td>
<td>0.04</td>
<td>0, 0.5</td>
<td>0.0</td>
<td>0</td>
</tr>
<tr>
<td>Physical force</td>
<td>458</td>
<td>0.89</td>
<td>0.13</td>
<td>0, 1</td>
<td>0.86</td>
<td>0.96</td>
</tr>
<tr>
<td>Mechanical force</td>
<td>458</td>
<td>0.09</td>
<td>0.12</td>
<td>0, 1</td>
<td>0.02</td>
<td>0.12</td>
</tr>
<tr>
<td>Deadly force</td>
<td>458</td>
<td>0.01</td>
<td>0.05</td>
<td>0, 0.5</td>
<td>0.0</td>
<td>0</td>
</tr>
<tr>
<td>Diversity Index</td>
<td>458</td>
<td>0.16</td>
<td>0.12</td>
<td>0, 0.53</td>
<td>0.07</td>
<td>0.24</td>
</tr>
<tr>
<td>Municipal level</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estimated population</td>
<td>458</td>
<td>18623.93</td>
<td>25771.41</td>
<td>269, 279,812</td>
<td>5454</td>
<td>22,200</td>
</tr>
<tr>
<td>Mean crime rate, per 1000</td>
<td>458</td>
<td>19.34</td>
<td>17.77</td>
<td>1.66, 151.98</td>
<td>8.30</td>
<td>23.21</td>
</tr>
<tr>
<td>Rural</td>
<td>458</td>
<td>0.16</td>
<td>0.37</td>
<td>0, 1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Suburban</td>
<td>458</td>
<td>0.50</td>
<td>0.50</td>
<td>0, 1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Urban</td>
<td>458</td>
<td>0.331</td>
<td>0.47</td>
<td>0, 1</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Note.

1 Only one department reported that they had no education requirements. This department was collapsed into the category “high school.”

2 In incidents where an officer resorts to using more than one type of force, the most lethal type of force is measured in a single use of force incident.

3 Data for education requirements and race/ethnicity were obtained from LEMAS. LEMAS only reported on 121 departments, including Sheriff’s Offices. Of the 121 departments, 114 departments were included in the Force Report.

3 The New Jersey State Police and two departments were deleted from the analysis due to missing data on key variables leading to a sub-sample of 458 departments.

**Diversity Index.** The measure used to evaluate specialization and versatility in force at the department level is the diversity index. The diversity index is derived from Agresti
and Agresti (1978), who first applied it to determine species diversity. It provides an estimate of the “probability that two individuals selected at random from the population would be in different categories” (p. 206). The diversity of offending index has since been used to understand offending onset and specialization (Piquero et al., 1999), compare specialization and versatility in the criminal career of individuals in various subgroups (Mazerolle et al., 2000), measure the magnitude of specialization in a sample of serious offenders (Sullivan et al., 2006), and evaluate the extent to which the propensity to offend, and changes in local life circumstances impact patterns of offense specialization/versatility (McGloin et al., 2007).

Scholars that have applied the diversity index have argued that it is advantageous over other measures as 1) it does not rely on the consecutive ordering of offenses (i.e., the order that officers use force), and 2) it is an individualized measure of offending patterns over time. The formula for the diversity index is below:

\[
\text{Diversity Index (D)} = 1 - \sum_{i=1}^{k} p_i^2
\]

Where \( p \) equals the proportion of force incidents in category \( k \), \( k \) classifies the number of force incidents in the data categories (e.g., constructive force; physical force, mechanical force, and deadly force), and \( p_i \) represents the proportion of observations in the \( i \)th category. The diversity index ranges from a minimum value, where \( D = 0 \) indicates complete specialization in a specific use of force category, to a maximum value, where \( D = 0.75 \) \((D_{\text{max}} = (4-1)/4^{10}) \) indicates complete versatility in the use of force behaviors.

Though the index has shown to be useful for understanding specialization and versatility in criminal behavior, a limitation of using the diversity index is whether the
maximum value and interpretation of D are confounded by offense frequency (Agresti & Agresti, 1978; McGloin et al., 2007; Osgood & Schreck, 2007; Sullivan et al., 2006) as “specialization inherently connotes some notion of proportion” (McGloin et al., 2007, p. 328). For example, it has been argued that the offense frequency is related to values of D given that the “number of offense categories artificially inflates the ceiling of the observed D” (Osgood & Schreck, 2007; Sullivan et al., 2006, p. 208). However, Sullivan et al. (2006) concluded that “D” values are not artifacts of the number of crimes an offender commits, given that the number of offenses does not necessarily demonstrate diversity or specialization. Instead, a person can be involved in relatively few incidents but still show specialization or versatility in offending patterns (p. 208-209). Similarly, Agresti and Agresti (1978) noted that: “if the groups have different numbers of categories, however, and we believe that a large number of categories contributes to greater diversity, then we would wish to use the unstandardized index D . . . basically D is a function of both the number of categories and the dispersion of the population among the categories,” (p. 208). Agresti and Agresti (1978) advised against using standardizing values of D to resolve these concerns along these lines.

**Analytical Strategy**

To capture the full breadth of data, bivariate and multivariate analyses are applied to the sample of 458 departments and the subset of 114 departments separately. The analytical strategy for this study is twofold. First, to compare diversity indices across the variables of interest, Pearson’s r correlation statistics are employed to determine whether variables of interest are associated with specialization (or versatility) of force in departments at the bivariate level. Pearson’s r is the best method for measuring the association between two
continuous variables of interest, as it captures the magnitude of the association and the
direction of the association. The Pearson correlation can vary from −1 to 1, with 1
indicating a strong positive relationship, -1 indicating a strong negative relationship, and a
zero indicating no relationship. As a result, the Pearson’s r evaluates whether the diversity
index from one sample is ranked higher than the other sample’s diversity index.

For the multivariate models, the study takes a similar approach to Mazerolle et al.
(2000), McGloin & Rowan (2015), and Sullivan et al. (2006) to test whether a series of
variables that tap into the composition of departments as well as environmental contexts
are associated with the specialization in force. The diversity measure, however, poses some
challenges as it violates assumptions of ordinary least squares regressions. For example,
the index is slightly skewed and bounded (from 0 to 1), potentially introducing bias in the
estimates. For this reason, this study, similar to the studies above, employs a Tobit
regression, as it “provides consistent estimates of parameters governing the distribution of
a censored normal random outcome variable” (Smith & Brame, 2003, p. 365 see also Long,
1997; Tobin, 1958). Precisely, the Tobit estimator captures two types of effects “1) the
effect on the values of the dependent variable for cases with a non-limit […] value on the
dependent variables, and 2) the effect on the probability of having a non-limit value for
cases with the limit value of the dependent variable” (Roncek, 1992, p. 503).

However, an assumption of the Tobit estimator is proportionality. Proportionality
assumes that the process that produces variation in the censoring outcome is the same as
the process that produces variation in the noncensored cases (Blaylock & Blisard, 1992;
Roncek, 1992; Smith & Brame, 2003). Because the Tobit restricts coefficients to the same
direction and magnitude, it can be misspecified if the assumption of proportionality is not
met (Blaylock & Blisard, 1992; Roncek, 1992; Smith & Brame, 2003). In this case, Smith and Brame (2003) proposed an alternative model, the Cragg specification, in which the “probability of a limit observation is independent of the regression model for the non-limit data” and thus relaxes the assumption of proportionality (also see Sullivan 2006, p. 207).\(^\text{11}\) Instead, the Cragg specification evokes a method in which a decision equation is modeled as both a probit and a regression model, such as a truncated regression, for non-limit observations (Cragg, 1971; see also Lin & Schmidt, 1984; Sullivan et al., 2006).

To test the proportionality, a test statistic can be calculated by estimating a Tobit, probit, and truncated regression model with all the same indicators. This test statistic is distributed as a chi-square with degrees of freedom that equal the number of parameters in the base model. Subsequently, the difference in the degrees of freedom between the probit and truncated degrees of freedom is subtracted from the Tobit degrees of freedom (see McGloin & Rowan 2016; Smith and Brame, 2003; Sullivan et al., 2006). The equation follows:

\[
\text{chi-square} = -2\left[\ln L_T - \left(\ln L_P + \ln L_{TR}\right)\right]
\]

Where \(L_T\) is the likelihood of the Tobit model, \(L_P\) is the likelihood for the probit model, and \(L_{TR}\) is the likelihood for the truncated regression model, with all models generated separately. If the test statistic exceeds the critical value of the chi-square distribution, where degrees of freedom is equal to the number of variables in the model including a constant, then the Tobit model is rejected, and the Craig specification, where interpretations are restricted to the probit and truncated regression coefficients, is preferred.

\(^{11}\) The Cragg “relaxes the constraint that the coefficients governing whether or not an individual is censored are directly proportional to the coefficients governing the score on the outcome variable given that an individual is not censored” (Smith and Brame, 2003, p. 368-369).
Results

The distribution of the diversity index is shown in Figure 12. The diversity index ranges from 0 (complete specialization) to 0.53, with a median of 0.15. On average, departments had a diversity index of 0.16 (SD = 0.12). Of the 458 departments, 15% (n=67) showed complete specialization in the use of force, whereas 45% (n=208) of departments fell above the mean, ranging from an index of 0.16 to 0.53.

Figure 12. Distribution of the Diversity Index

Bivariate results

To provide an overview of the key variables of interests and their association with specialization (or versatility) of force at the bivariate level, Figure 13 and Figure 14 summarizes the results of the correlation matrix. Figure 13, including 458 departments, outlines four key findings. First, the diversity index is positively associated with the size of the department (r=0.10, p<0.05) and the volume of force in the department (r=0.12, p<0.05). As defined by the volume of force reports, more sustained use of force suggests
greater diversity in force patterns. This finding is consistent with the criminal career literature, where offense versatility tends to increase with offense frequency (Chaiken & Chaiken, 1982; Le Blanc & Loeber, 1998), and theory (Moffitt, 1993) that suggests a relationship between offending frequency and versatility. Second, there is a positive association between the diversity index, the estimated population \((r=0.11, p<0.05)\), and the municipality crime rate \((r=0.11, p<0.05)\). Indeed, in more populated areas and areas that have higher crime rates, departments exhibit greater versatility in force, such that they may exhibit a combination of constructive, physical, mechanical, and deadly force. This is important and aligns with Klinger’s (1997) work, among many others, where it has been suggested that the neighborhood’s environmental makeup determines how police respond to crime in these neighborhoods. Overall, it is important to note that these correlations are relatively small in magnitude.

Third, while some have argued that the department/organizational size is positively associated with effective policing (Greenberg et al., 1983; Klinger 1997; MacDonald, 2002) - insinuating that larger police departments may be less susceptible to police misconduct - others have found a positive association between organizational size and police misconduct, underlining the difficulty that larger agencies may have in managing and controlling officers' behaviors. (Eitle et al., 2014; Goel & Nelson, 1998). Yet, overall, less is known about the association between size and volume of force. The bivariate analysis suggests a strong positive association between the department’s size and the volume of force \((r=0.77, p<0.05)\). It also finds a positive association between the department's size and the crime rate \((r=0.17, p<0.05)\). Finally, when it comes to the sex/gender composition of the departments, there is a negative association between
departments with a higher proportion of sworn full-time male officers and volume of force (r=−0.32, p<0.05), crime rate (r=−0.17, p<0.05) and the use of deadly force (r=−0.16, p <0.05).

![Correlation Matrix](image)

**Figure 13. Pearson’s r correlation matrix (n = 458)**

Turning to Figure 14, which samples on a subset of 114 departments but captures additional measures on race/ethnicity and education requirements obtained from LEMAS, there are three main observations. First, bivariate results suggest a positive association between the diversity index with the size of the department (r=0.19, p<0.05), the volume of force in the department (r=0.22, p<0.05), as well as the estimated population (r=0.014, p<0.05) and crime rate (r= 0.23, p <0.05) of the municipality. This pattern is consistent with results sampling on 458 departments. However, there seems to be no association
between the department’s racial/ethnic composition, education requirements, and the diversity index.

Next, there is a relatively strong and positive association between the size of the department and volume of force ($r=0.66$, $p<0.05$), which is also consistent with the model above. Lastly, honing on the association between department size and diversity in race/ethnicity and sex of sworn full-time officers in the department, there is a negative association between the size of the department and the proportion of sworn full-time male officers ($r=-0.46$, $p<0.05$), White officers ($r=-0.49$, $p<0.05$), and a positive association between the size of the department, and proportion of sworn fulltime Black ($r=0.34$, $p<0.05$) and Hispanic officers ($r=0.39$, $p<0.05$) employed. While we have to be relatively cautious in over-interpreting bivariate associations, the positive association does allude to diversity in larger departments. However, diversity in race/ethnicity and sex is not necessarily associated with lower volumes of force, with a positive association between the volume of force and departments that employ a higher proportion of full-time sworn female officers ($r=0.36$, $p<0.05$), Black officers ($r=0.22$, $p<0.05$) and Hispanic officers ($r=0.39$, $p<0.05$). Finally, there is a positive association between the department’s education requirements ($r=0.22$, $p<0.05$) and the proportion of White sworn full-time officers in the departments, suggesting that departments that require higher levels of education have a higher proportion of White officers.\(^\text{12}\)

\(^{12}\) Education level was re-coded as a continuous variable where 1 = no requirements/ high school, or equivalent; 2= associate degree/equivalent, and 3= some college, bachelor’s degree, or equivalent.
Note. The map shows correlation coefficients for all pairs of variables (with deeper colors representing stronger correlations). Correlations not significantly different from 0 are in a white box. \(p<0.05\)

**Figure 14. Pearson’s r correlation matrix (n = 114)**

**Multivariate results**

The multivariate models are provided for both the Tobit (Blaylock & Blisard, 1992; Long, 1997; Maddala, 1983; Roncek, 1992; Tobin, 1958) and the Cragg specification (Cragg, 1971; Lin & Schmidt, 1984; Smith & Brame, 2003). In the first model, where all 458 departments are included in the analyses, the chi-square test of 54.16 exceeds the critical value of 14.07 with 7 degrees of freedom (including the constant). Therefore, we reject the proportionality assumption and conclude that the Tobit model is inappropriate in favor of the two-equation Cragg specification. Similarly, in the second model, where 114 departments are included in the analyses, the chi-square test of 34.40 exceeds the critical
value of 19.68 with 11 degrees of freedom (including the constant). Thus, for both models, interpretations are restricted to the probit and truncated regression coefficients.

According to Table 6, two variables emerge as significant: volume of force and crime rates per 1000 civilians. In the probit model, departments that reported a higher volume of force were more likely to measure a non-zero on the use of force diversity index, net of all else (b=0.71, p <0.001). These departments were more likely to generate higher diversity index values and have higher versatility in force behaviors. However, this effect is non-significant in the truncated regression (b=0.009, n.s.). Next, across all models, and specifically turning to results from the probit (b=0.297, p<0.001) and truncated regression (b=0.022, p<0.05) models, departments in municipalities with higher crime rates per 1000 civilians were significantly likely to show greater diversity in their use of force patterns and thus less likely to measure zero on the index net of all else.
Table 6. Coefficient estimates, Diversity Index (n=458)

<table>
<thead>
<tr>
<th></th>
<th>OLS Regression</th>
<th>Tobit</th>
<th>Probit</th>
<th>Truncated Regression</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size of department</td>
<td>-0.000</td>
<td>-0.007</td>
<td>0.107</td>
<td>-0.000</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.013)</td>
<td>(0.211)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Volume of force</td>
<td>0.009</td>
<td>0.022***</td>
<td>0.714***</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.008)</td>
<td>(0.101)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Proportion Male (ref: Female)</td>
<td>0.013</td>
<td>0.031</td>
<td>-0.413</td>
<td>0.013</td>
</tr>
<tr>
<td></td>
<td>(0.125)</td>
<td>(0.144)</td>
<td>(1.957)</td>
<td>(0.124)</td>
</tr>
<tr>
<td>Crime rate, per 1000</td>
<td>0.022***</td>
<td>0.024**</td>
<td>0.297**</td>
<td>0.022**</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.139)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Suburban (ref: Rural)</td>
<td>-0.017</td>
<td>-0.015</td>
<td>0.033</td>
<td>-0.017</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.019)</td>
<td>(0.253)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Urban Center (ref: Rural)</td>
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<td>-0.007</td>
<td>-0.057</td>
<td>-0.009</td>
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<td></td>
<td>(0.019)</td>
<td>(0.021)</td>
<td>(0.301)</td>
<td>(0.018)</td>
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<tr>
<td>Tobit ancillary parameter</td>
<td>0.019***</td>
<td></td>
<td></td>
<td>0.122***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td></td>
<td></td>
<td>(0.004)</td>
</tr>
<tr>
<td>Truncated regression sigma</td>
<td></td>
<td></td>
<td></td>
<td>0.122***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.004)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.083***</td>
<td>0.038</td>
<td>2.173***</td>
<td>0.083***</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.036)</td>
<td>(0.594)</td>
<td>(0.031)</td>
</tr>
<tr>
<td>LLL</td>
<td>154.85</td>
<td>-133.11</td>
<td>315.04</td>
<td></td>
</tr>
</tbody>
</table>

Note.

1 Variables were log-transformed before analyses.
2 The estimated population of the municipality was removed from the model due to issues of multicollinearity. Once removed, variance inflation factors were < 5 with a mean of 1.99, indicating that multicollinearity was no longer an issue in this model.
3 Breusch-Pagan / Cook-Weisberg test for heteroscedasticity p = 0.26, indicating that heteroscedasticity is not present in the data.
4 Standard errors (SE) are presented in parentheses.
*** p<0.01, ** p<0.05, + p<0.1

In Table 7, two variables emerge as significant: volume of force and proportion of sworn full-time Black officers (in comparison to White officers). First, consistent with Table 6, in the probit model (b=1.141, p<0.001), departments that reported higher volumes of force were more likely to show greater versatility in using force, indicating that higher frequency leads to higher diversity, net of all else. As in Table 6, this effect is non-significant in the truncated regression results (b=0.011, n.s.). Second, results from the truncated regression (b=0.016, p<0.05) indicate that departments that employ a higher
proportion of Black officers, compared to White officers, measure higher on the diversity index, signaling greater versatility in force behaviors, net of all else. However, this effect is marginally significant in the probit model (b= 0.411, p< 0.10).
Table 7. Coefficient estimates, Diversity Index (n=114)

<table>
<thead>
<tr>
<th></th>
<th>OLS Regression</th>
<th>Tobit</th>
<th>Probit</th>
<th>Truncated Regression</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size of department</td>
<td>-0.010</td>
<td>-0.018</td>
<td>-0.627</td>
<td>-0.010</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.021)</td>
<td>(0.560)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Volume of force</td>
<td>0.011</td>
<td>0.023+</td>
<td>1.141***</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.013)</td>
<td>(0.350)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Proportion Male (ref:</td>
<td>0.250</td>
<td>0.238</td>
<td>-0.933</td>
<td>0.250</td>
</tr>
<tr>
<td>Female)</td>
<td>(0.215)</td>
<td>(0.231)</td>
<td>(4.974)</td>
<td>(0.205)</td>
</tr>
<tr>
<td>Proportion Black (ref:</td>
<td>0.016**</td>
<td>0.019**</td>
<td>0.411+</td>
<td>0.016**</td>
</tr>
<tr>
<td>White)</td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.234)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Proportion Hispanic (ref:</td>
<td>0.002</td>
<td>0.001</td>
<td>0.020</td>
<td>0.002</td>
</tr>
<tr>
<td>White)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.148)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Proportion Other (ref:</td>
<td>-0.005</td>
<td>-0.005</td>
<td>-0.009</td>
<td>-0.005</td>
</tr>
<tr>
<td>White)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.159)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Degree required (ref:</td>
<td>0.022</td>
<td>0.024</td>
<td>0.006</td>
<td>0.022</td>
</tr>
<tr>
<td>High school)</td>
<td>(0.029)</td>
<td>(0.031)</td>
<td>(0.679)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Crime rate, per 1000</td>
<td>0.018</td>
<td>0.012</td>
<td>-0.788</td>
<td>0.018</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.024)</td>
<td>(0.573)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Suburban (ref: Rural)</td>
<td>0.020</td>
<td>0.036</td>
<td>0.976</td>
<td>0.020</td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td>(0.043)</td>
<td>(0.690)</td>
<td>(0.037)</td>
</tr>
<tr>
<td>Urban Center (ref: Rural)</td>
<td>0.022</td>
<td>0.036</td>
<td>0.963</td>
<td>0.022</td>
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<tr>
<td></td>
<td>(0.038)</td>
<td>(0.042)</td>
<td>(0.742)</td>
<td>(0.036)</td>
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<tr>
<td>Tobit ancillary parameter</td>
<td>0.014***</td>
<td></td>
<td></td>
<td>0.105***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td></td>
<td></td>
<td>(0.007)</td>
</tr>
<tr>
<td>Truncated regression sigma</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.143</td>
<td>0.118</td>
<td>2.678</td>
<td>0.143</td>
</tr>
<tr>
<td></td>
<td>(0.105)</td>
<td>(0.112)</td>
<td>(3.089)</td>
<td>(0.099)</td>
</tr>
<tr>
<td>LLLL</td>
<td>60.35</td>
<td>-17.68</td>
<td>95.23</td>
<td></td>
</tr>
</tbody>
</table>

Note.
1 Variables were log-transformed before analyses.
2 The estimated population of the municipality was removed from the model due to issues of multicollinearity. Once removed, variance inflation factors were < 5 with a mean of 2.07, indicating that multicollinearity was no longer an issue in this model.
3 Breusch-Pagan / Cook-Weisberg test for heteroscedasticity p = 0.35, indicating that heteroscedasticity is not present in the data.
4 Standard errors (SE) are presented in parentheses.
*** p<0.01, ** p<0.05, + p<0.1
Discussion

The criminal career framework is an important descriptive tool for organizing and unifying patterns of criminal behavior (Blumstein et al., 1988; Blumstein & Cohen, 1987). For example, rather than treat force as an “undifferentiated unitary phenomenon,” the criminal career approach distinguishing officers from the types of force they use and partitions departments by providing separate estimates (Blumstein et al., 1988). This is consistent with more recent applications where researchers have shifted from measuring police use of force as a dichotomous variable and have focused on variations in types of force (Garner et al., 1995; Smith et al., 2007; Lawton, 2007; MacDonald et al., 2009; Terrill & Paoline, 2017). It also warrants calls to better understand departmental culture (Ingram et al., 2013, 2018) structure and environmental context as it pertains to officer activity with Klinger (1997) stating, “few studies have considered the possibility that police action might vary across urban neighborhoods . . . but none contains any systematic theory linking police activity to the ecological contexts in which it occurs” (p. 278). This approach to studying specialization and versatility in officer use of force, thus adds to our understanding of how departmental characteristics and environmental features influence differential patterns of policing and further highlights the importance of opportunity structures and discretion in police activity.

What is distinct in this study is that results suggest specialization in force more than they do versatility within departments. The average diversity index was 0.16, out of a maximum value of 0.75, with the diversity index ranging from 0.0 to 0.53. While the most convincing argument for specialization would have been a diversity index of 0, nonetheless, departments in New Jersey evidenced a considerable amount of specialization
with regards to their force usage. This is not surprising, given how rare force, especially the use of more severe force, is (Terrill & Paoline, 2017). It follows that when officers use force, they rely on tactics at the lower end of the force spectrum, such as physical force (Bayley & Garofalo, 1989; Garner et al., 1995, 2002; Garner & Maxwell, 1999; Pate et al., 1993). Indeed, across the 458 departments, 89% of force reported was categorized as physical force. Of the 67 departments that showed complete specialization, sixty-two departments specialized in physical force. Nevertheless, while this study applies the Attorney General’s definition of physical force, other studies have even found variations in degrees of physical force applied (Garner & Maxwell, 1999).

Next, evaluating variations in force between departments, a limited number of variables at the organizational level were associated with versatility in force in Table 6, with a sample of 458 departments, and Table 7, with a subset of 114 departments. First, net of department size, hiring requirements, officers’ composition, and characteristics of the municipality, a key finding was the positive association between volume of force and the diversity index. Notably, as the volume of force increases, so does versatility in the types of force used. This aligns with the criminal career perspective, which predicts a positive relationship between offense frequency and versatility. For example, studies on offending behavior have found significant versatility in offending over time, and only a modest tendency for offenders to repeat the same kind of offense (Farrington et al., 1988; Gottfredson & Hirschi, 1990; Lattimore et al., 1994; Le Blanc & Loeber, 1998).

It may be the case that departments that report higher volumes of force provide greater discretion, and perhaps more motivation, for officers to exercise coercive authority than departments that report lower volumes of force. Indeed, when force occurs in more
regularity, officers not only have greater opportunities to exert various types of control over civilians, but force usage may be an informal aspect of the organization linked to peer culture (Ingram et al., 2018). This is proposed by Hunt (1985), where the author suggests that “the experienced “street cop” becomes an expert at using techniques of neutralization to characterize the use of force on the streets, at judging its use by others, and at evaluating the necessity for using force by standards those techniques provide” (p.339). Indeed, various techniques of neutralization (Sykes & Matza, 1957) may be more likely among officers in a department that exercises higher levels of volume, with officers becoming less discerning with the kinds of force they are willing to use (Waegel, 1984).

Second, the environment shapes and influences police use of force. However, this finding only pertains to Table 6, including 458 departments, with no measures on officer race/ethnicity and departmental educational requirements. Findings suggest that departments in municipalities with higher crime rates were more likely to exhibit versatility in force. Indeed, in high crime areas, officers may come in regular contact with a greater number of civilians whom they deem as “violent,” “unpredictable,” or “suspicious,” and thus acclimate their force usage, moving beyond the use of physical force. For example, Klinger (1997) maintained that “officers view citizens who live in higher crime areas as generally less worthy than those who reside in less crime-filled districts” (p. 291). This was confirmed by Lee et al. (2014), such that the authors found a significant effect of neighborhood violent crime rates on officers selecting to use more and higher levels of force across eight different cities. Along these lines, it stands that higher levels of force – and in our case, force that goes beyond physical and includes a range of constructive, mechanical, and deadly force – may be more likely when officers perceive higher risks of
danger or threats to their safety, and when they perceive civilians as more deserving of force (Klinger, 1997; Mastrofski et al., 2002; White, 2003).

Finally, in Table 7, departments with a higher proportion of Black officers, relative to White officers, were likely to exhibit versatility in force net of department size, the volume of force, hiring requirements, and municipality characteristics. The “community accountability theory” (Reiss, 1971) suggests a way to reduce animosity between the police and minority citizens is by hiring more minority officers (Smith & Holmes, 2003). However, racial and ethnic minorities tend to disproportionately concentrate in areas of social disorder, with studies finding that civilians encountered in these areas are more likely to experience force and higher levels of force (Fagan & Davies, 2000; Smith 1986). Perhaps efforts to diversify police agencies, with departments employing a higher proportion of Black officers to reduce social distance and racial tensions, may be prompting relational tensions between the police and civilians (Brunson & Gau, 2015; Levin & Thomas, 1997). Indeed, officers in these departments may have more opportunities to use various levels of force because they come in greater contact with civilians who tend to be more resistant or are perceived as “deserving of force” (Klinger, 1997; Mastrofski et al., 2002; Van Maanen, 1978b).

With additional controls for the racial/ethnic composition of departments and educational requirements, the crime rate is non-significant in Table 7. This is compared to Table 6; wherein there was a larger sample size and no measure of the department's racial/ethnic composition. Given the relatively small sample size of 114 departments, these findings should be interpreted with extra caution. Any comparisons between Table 6 and Table 7 should be limited.
Key Challenges and Implications

The police officer’s discretion to use force, or the threat of force, is the most defining characteristic of the police role (Bittner, 1970). Yet, it is not surprising that features of police organizations impact what officers do, and how they behave varies across ecological space (Klinger, 1997). While the current study provides a basis for understanding variations in police use of force, it has several limitations that suggest caution in interpreting results.

First, there may be omitted variable bias, especially in Table 6 as data on the race/ethnicity and educational requirements from LEMAS were not available for all 458 departments, but only a subset of 114 departments. More generally, this speaks to larger issues such as the lack of utility and uniformity of data collected by and from law enforcement agencies nationwide. This is an important issue as the ability to understand prevalence and patterns of use of force is dependent on the availability of data. Limited information on departments and officers employed within these departments impacts the robustness and accuracy of findings and potentially masks greater variation in policing styles across agencies. Ideally, given that departments in New Jersey follow similar laws, guidelines, and policies to report (i.e., Attorney General Guidelines), only a few organizational features vary across departments that are not accounted for by the current study. Future research should look to collect measures that capture more formal and informal characteristics of departments. This would provide a thorough depiction of the association between variations in use of force and department characteristics.

Second, an organizational and occupational characteristic of departments that should be measured is departmental culture. While many studies have underlined the link
between police culture and police use of force, others have argued that there is no monolithic culture as culture varies across departments and workgroups (Ingram et al., 2013, 2018; McCluskey et al., 2005). In the current study, culture is argued to be a collective property – an element of the police role shared by officers in the same occupational and organizational working environment - but is not measured. Future studies should capture measures of cultural strength across departments to evaluate if variations in adherence to police culture are associated with specialization and versatility in use of force.

Third, the study is unable to incorporate, in more detail, other contextual factors at the municipality level. For example, Black (1976) argues that the amount of law applied against civilians will vary based on the characteristics of the officer and civilian in an interaction, whereas other studies find no link. To address possible associations, or to discount the association, between types of police use of force and neighborhood contexts, future studies should incorporate neighborhood racial composition, socioeconomic status, residential stability, and levels of social disadvantage.

Finally, the diversity index is a measure of specialization and versatility in force usage. However, it does not allow us to compare excessive force across departments or the link between excessive or higher degrees of force and departmental and environmental context. It may be a fruitful line of inquiry to examine the association between the diversity index and excessive use of force and misconduct complaints. For example, are departments that specialize in physical force more likely to generate excessive use of force and misconduct complaints, net of all else? Alternatively, are agencies that exhibit versatility in force more likely to generate excessive use of force and misconduct complaints, net of
all else. Whether force is excessive or not, force should not be minimized or depicted as mere responses to external situations or routine policing practices.

Addressing the collective nature of force by understanding differences between departments that specialize in force versus departments that use a variety of force has important practical implications. For example, suppose environmental features are associated with the use of force. If officers are more forceful in areas characterized by high levels of disadvantage and crime irrespective of suspect behavior, it would call for departments to re-group and re-evaluate departmental values placed on transparency and accountability to the law. Conversely, it might be useful to pay attention to the volume of force emanating from departments as this impacts the type and degree of force used. Such efforts might begin with a better understanding of socialized beliefs in the department, such as officers’ views of the police role, the organization, and the neighborhood they serve. Departments may mobilize dialogue about using force to distinguish between those in the department who understand the conditions for which force is reasonable or necessary and those who do not (Hunt, 1985).

Officers’ views of organizational and occupational culture not only cultivate a group identity, but widespread perceptions are reinforced and diffused to others through formal and informal interactions on and off the job. When departments have informed information about collective patterns of behaviors in their department, not only can they better adjust (and re-adjust) their organizational structure, but they can tease out any socialization and peer effects that may negatively influence the behaviors and perceptions of members.
STUDY 3. BEYOND THE “BAD APPLE”: A NETWORK APPROACH TO IDENTIFYING FOCAL OFFICERS

Networks play a foundational role in understanding criminal and non-criminal influences on behaviors (Christakis & Fowler, 2007; Haynie, 2002; Papachristos, Wildeman, et al., 2015; Valente, 2012; Warr, 1993; Wasserman & Faust, 1994). Group-based violent intervention strategies and crime control policies have applied network approaches to various types of data (arrest data, field reports, firearm/shooting data) for both investigative purposes and as a means to reduce and control crime (Braga & Weisburd, 2012; Engel, 2008; Kennedy, 1996). Many of these strategies, which are rooted in a focused deterrence approach, have stressed the importance of identifying “key actors” to prevent crime and reduce future criminality. Indeed, these strategies capitalize on the grouped nature of crime and violent behaviors by 1) intervening on key actors, such that they are unable to participate in future violent and criminal activity (i.e., arrests, removal), 2) intervening on key actors by offering social service and community programs, or 3) relying on key actors to serve as “credible messengers” who communicate the potential consequences of crime and violent behaviors to those who share in their social and spatial space (Alpert & Smith, 1994; McGloin, 2005; Morselli, 2010; Schwartz & Rouselle, 2009; Valente, 2012; Wheeler et al., 2019). All avenues exert social pressures on the actor(s) and the broader network of members who may be directly or indirectly tied to these actors (Borgatti, 2006).

The policing organization presents a particularly novel environment to apply problem-oriented strategies where specific recurring problems, such as force, are analyzed to identify focal officers with at-risk profiles. Police officers are tasked with complicated and often dynamic undertakings, allowing them the opportunity to use and abuse their power (Klinger & Brunson, 2009). At the same time, there are several reasons to believe
that the potential for officer misconduct or excessive use of force may spread through conduits similar to the processes described for offenders. Like many repeat offenders that operate in close spatial and social proximity to one another, the policing profession’s structural and interdependent nature presents a persuasive case that “police work is group work” (Zhao & Papachristos, 2019, p. 90). Most officers work in close spatial and social proximity to one another. As such, police behaviors, and specifically, police violence, tends to be unevenly distributed (Alpert & Walker, 2000; Brandl et al., 2001; Edwards et al., 2019; Harris, 2010; Lersch & Mieczkowski, 1996) and shared through officers’ interactions, repeated observations, and exposure to common features of their workplace environment (see Ouellet et al., 2019; Wood et al., 2019; Quispe-Torreblanca and Stewart, 2019; Roithmayr, 2016). Therefore, similar to focused deterrence approaches where offender networks are used for crime reduction strategies, officer networks can be “leveraged to accelerate behavior change, improve organizational efficiency […] and improve dissemination and diffusion of innovations” (Valente et al., 2009, p. 49).

The current study capitalizes on the “networked” nature of police uses of force, building on study 1, where force was shown to be centralized, to identify high-risk officers situated with densely knit local groups. First, it applies community detection (i.e., Leiden algorithm) to uncover whether local groups conceal a more complex set of interactions among the broader network of officers that have used force together. Second, it identifies high-risk officers by applying a singular measure of network capital to distinguish between officers within the broader network. High-risk (i.e., focal) officers are defined as those involved in multiple use of force incidents with a greater number of colleagues, such that they may act as both “opinion leaders” (i.e., directly use force with many officers) and
brokers (i.e., connects officers, who otherwise might not connect, through use of force behaviors). Provided that much of the research acknowledges that problematic police behaviors are accounted for by a handful of “bad apples” embedded in “bad barrels” (Alpert & Smith, 1994; Alpert & Walker, 2000; Brandl et al., 2001; Kish-Gephart et al., 2010; McCluskey et al., 2005) identifying, or otherwise preventing, patterns of risky behaviors before they lead to future allegations of misconduct and excessive use of force complaints is an important first step for implementing preventive measures. These measures may not only deter problematic behaviors and promote accountability, but they can be customized to local conditions and operational capacities. The study concludes with a discussion of intervention and prevention strategies that have shown relative success in mobilizing behavioral shifts in groups of officers (i.e., bad barrels) and individual officers (i.e., bad apples).

The concentrated nature of officer behaviors

Like other forms of criminal and violent behaviors, the assertion that a small number of police officers are disproportionately responsible for misconduct, excessive use of force complaints, and more broadly, problematic behaviors have received considerable traction over the last several decades (Alpert & Walker, 2000, p. 200; Brandl et al., 2001; Harris, 2010; Kish-Gephart et al., 2010; Rozema & Schanzenbach, 2019). For example, in a systematic study of early warning systems, Walker et al. (2001) noted that “as few as 2 percent of all officers are responsible for 50 percent of all citizen complaints” (p.1). An analysis of complaints against the Miami Police Department found that 5% of officers accounted for 25% of all complaints (Alpert & Walker, 2000), and a study of officers in New York City found that officers who were terminated for causes such as police crime,
police corruption, or abuse of authority were more likely to have civilian allegations (Kane & White, 2009). More recently, Wood, Roithmayr, and Papachristos (2019) shed light on the grouped nature of officer misconduct, finding that among officers employed by the CPD from 2010 to 2016, the “top 1 percent of officers received a civilian co-complaint with 26 other officers and a departmental complaint with 14 other officers, on average” (p. 10).

Because officers tend to conduct their daily work in small groups of similarly situated personnel, the importance of the peer group and the salience of officers’ networks should not be lost. Indeed, police officers are subjected to peer influence and informal control, impacting how officers learn to do their job and their behaviors on the street (Alpert & Dunham, 2004; Chappell & Piquero, 2004; Crank, 1998; Fagan & Geller, 2015; Roithmayr, 2016). For example, Fagan and Geller (2015) found that as Terry stops increased in New York from 2004 to 2012, so did the reliance on a small number of factors to justify such stops by the police. In what they called “scripts of suspicion,” the authors found that officers in the same unit were likely to rationalize and justify their stops using shared narratives specific to the suspect’s race and neighborhood factors (p. 55). Specifically, the authors argued that officers were learning from, and reinforced by, one another’s behaviors to the point that these narratives became ineffective and signaled a collective mentality that no longer complied with law enforcement requirements or the law.

Conversely, Hunt (1985) argued that the peer group influences levels of force employed against suspects. The group indicates what behaviors are appropriate for dealing with situations (also see Worden, 1996a). For example, in a survey of police officers in San Antonio, Texas, Cancino (2001) found that 89% of the officers surveyed learned how to
use physical force from their peers on the force (p. 154). Even more pronounced, however, are findings that speak to officer responses to such behaviors. That is, if an officer observes another officer’s behavior, such as using force, leading to a positive reward, they are more likely to imitate and continue that behavior (Hunt & Manning, 1991; Roithmayr, 2016). Indeed, Chappell and Piquero (2004) echoed the imitative nature of officer behaviors, highlighting the importance of differential peer associations in accounting for police misconduct. They found that officers who believed their peers’ use of excessive force to be less severe were more likely to accumulate civilian complaints (p. 100), thereby reinforcing their argument that peer groups within departments “may facilitate deviant behavior by transmitting the beliefs, values, definitions, and manners of expression that depart from acceptable behavior” (p. 93). Taken together, the preceding studies, along with many others, have suggested that behaviors are likely to diffuse and be informally learned among officers who share ties.

**Networks as a means of intervention and prevention**

The focused deterrence approach directs targeted intervention and prevention strategies to an identified population, such as gang members, involved in a specific recurring type of crime, such as gun violence, with the intent to reduce serious violence and to discourage future crimes (Braga, 2008; Kennedy, 1996). Three main findings drive focused deterrence approaches (also known as “pulling levers”): 1) a relatively small number of offenders are responsible for the greatest number of crimes, 2) most violence is unevenly distributed in select homogenous populations, and 3) crime and violent behaviors are facilitated by those in close spatial and social proximity to one another (Braga, 2015; Braga et al., 2013; Braga & Weisburd, 2012; Corsaro et al., 2012, 2013; Kennedy, 1996; McGarrell et al., 2006;
By directing the strategic application of enforcement and social service resources on key actors in the network, these strategies have conventionally used traditional and nontraditional methods, such as social network analysis, to identify groups of high-risk individuals who either have significant influence over the offending population or likely to become victims of violence (Braga et al., 2001; Crandall & Wong, 2012; Engel et al., 2013; Papachristos et al., 2007).

Research using network analysis to identify the positional importance and attributes of members has conventionally focused on identifying key actors in the network through various centrality measures (Baker & Faulkner, 1993; Bright et al., 2015; Krebs, 2002; Morselli, 2010). These actors are optimally positioned as they have the potential to fragment the flow of the network, thus having the greatest bridging capacity between subgroups, or they may be central to the network (Borgatti, 2006; Duijn et al., 2014; Schwartz & Rouselle, 2009), making them particularly useful for intervention (Malm & Bichler, 2011; Morselli, 2010; Morselli & Roy, 2008; Wheeler et al., 2019).

Beyond network position, key actors may also acquire important roles and attributes (Bright et al., 2013). For example, in drug trafficking networks, “key actors” may be vital to its operation's success. These individuals may acquire the expertise, resources to control the market, and access to various roles (i.e., smuggling, supply, and financing) required for the crime commission process (Malm & Bichler, 2011). In a network of gang members, key actors may be responsible for outbreaks of violence in the community (Papachristos et al., 2007; Papachristos & Kirk, 2015) or those in charge of the gang's social organization and structure (i.e., leaders) (Venkatesh, 1997). This is to say that key actors will, and do, vary – their roles and overall importance to the network are conditional on
who is looking to identify these actors (e.g., gang leaders, law enforcement officials, stakeholders), the issue or concern they are seeking to address (e.g., network disruption, arrests, crime commission process) and the outcome(s) they are driven by (e.g., violence prevention, resource allocation, monetary gains).

Within the context of the use of force network, key actors in the network may escalate police violence. For example, Zhao and Papachristos (2020) consider how network position impacts officer-involved shootings. Using data of officer-related complaints collected by the CPD between 2000 and 2003, they examined whether officer’s brokerage roles, “where an officer is on the shortest path of associations that connect other pairs of officers,” were associated with subsequent shooting behavior between 2004 and 2016, net of officer demographics (Zhao & Papachristos, 2020, p. 90). They found that officers that fired their weapon at a civilian from 2004 and 2016 played a brokerage role in the network of co-complaints between 2000 to 2003. These officers were in a position to reach and be reached more quickly by others, net of their age, age at hire, race, sex/gender, activity, and career movement. Their findings contextualize how pathways and network structure can help understand police violence, specifically, how an officer’s position in the network can escalate misconduct and neutralize police violence (Muir, 1977; Waegel, 1984). These officers may ease the guilt of using force for those within their immediate network, providing informal instructions and reinforcements for when force is employed (Chappell & Piquero, 2004; Hunt, 1985; Hunt & Manning, 1991; Roithmayr, 2016; Waegel, 1984).

In the presence of strong peer effects, as demonstrated by research on policing culture (Britz, 1997; Chappell & Piquero, 2004; Hunt, 1985; McCluskey et al., 2005; Rahr & Rice, 2015; Stoughton, 2014), if officers, who are likely to resort to force and to do so
more frequently than their peers, are not identified and intervened on, the propensity for misconduct, excessive use of force, and corruption can become pervasive and organized within and between departments (Caldero & Crank, 2004; Chappell & Piquero, 2004). From a policy perspective, identifying officers who frequently use force and do so in partnership with many others may serve as an accountability and transparency tool that builds on current intervention programs in place (Shjarback, 2015). For example, it may improve early warning systems that identify select officers, who exhibit performance problems (i.e., misconduct, excessive use of force), by incorporating a broader range of indicators and points of intervention (Alpert & Walker, 2000; Shjarback, 2015; Walker et al., 2001). It may also lead to specific policy recommendations that focus on the structure of officers’ networks, with implications for officer partnerships and workgroups, training units, and avenues to improve the efficiency of monitoring and disciplining efforts.

The current study adopts a preventative approach by applying community detection analysis and a measure of network capital to identify groups of “focal officers” with high-risk profiles relative to their colleagues. Community detection analysis (i.e., Leiden algorithm) is used to delineate officer sub-groups from the larger use of force network, while network capital distinguishes high-risk officers from their colleagues. These officers demonstrate elevated levels of using force with their centrality in the network enabling them to reach other officers more efficiently and effectively.

**Data and Methods**

Given that the network structure impedes or enhances the spread of behaviors, if behaviors are likely to be relayed amongst officers, there needs to be a “path” that connects officers through multiple indirect or direct channels (Wasserman & Faust, 1994). In this capacity,
the current study focuses on the largest connected component in the use of force network (see Figure 1, network on the right).

The study proceeds in two steps: first community detection algorithm is applied to extract groups from the broader use of force co-involvement network. This approach is designed to delineate and uncover the characteristics of subgroups. Next, a measure of network capital is employed. It considers each officer’s connectivity and severity to discern groups of high-risk focal officers from the broader network. Network capital considers both the attributes of network members and their centrality scores. This is useful for two reasons. First, members or groups that contribute more to network capital may be considered more central and, thus, responsible for the commission of force behaviors. Second, selecting a particular member or a group high in network capital may exert more change in network structure given their positional importance.

**Community detection analysis**

Community detection analysis is used to evaluate the structure of the use of force co-involvement network. Community detection analysis is derived from the assumption that networks naturally divide into relatively dense cliques or clusters (i.e., groups, communities). These “clusters” correspond with meaningful conceptualizations of social groups, or homogenous cliques, where members are more likely to interact with one another over others within the larger network.

Theoretically, community detection draws on early scholars such as Simmel (1955) and Moreno (1941), who stressed the importance of social structure as emerging from a pattern of relationships. Methodologically, community detection quantifies the “intuitive concept of community structure” by arranging ties between actors into groups (Newman,
One of the most common methods used for community detection is called modularity. Modularity-based approaches partition network graphs into densely connected sub-groups with loose connections between groups. Namely, it identifies areas of structural homogeneity within the larger heterogeneous network graph (Girvan & Newman, 2002; Newman & Girvan, 2004; Ouellet & Hashimi, 2019). The degree to which a network graph can be partitioned into subgraphs is assessed via a modularity score. The modularity score is a weighted function that quantifies the fraction of edges within a group, minus the expected number in an equivalent network with edges placed at random (Newman, 2006). Modularity scores range from 0 to 1. The higher the modularity score, the stronger the division within that network (Newman, 2006).

While there are multiple modularity-maximization techniques like the Girvan–Newman (Girvan & Newman, 2002), Newman (Clauset et al., 2004), Louvain (Blondel et al., 2008), and Leiden (Traag et al., 2019), the most appropriate method depends on the most efficient solution for the data at hand. That is, one that provides the highest modularity score and greatest validity compared to other solutions. In the current study, the Leiden algorithm is applied to determine the structure and composition of cohesive subgroups in the use of force network. The Leiden algorithm is based on the Louvain algorithm. However, it is considered an improvement. It guarantees that clusters are well-connected and takes substantially less time to detect quality clusters. The Leiden algorithm consists of three phases: “(1) local moving of nodes, (2) refinement of the partition and (3) aggregation of the network based on the refined partition, using the non-refined partition to create an initial partition for the aggregate network” (Traag et al., 2019, p. 4).
Furthermore, the Leiden algorithm is a stable iteration. This implies that there are no subsets of the community that can be separated (e.g., nodes are well connected to their community and cannot be moved to a different community), and the quality of the partition is optimal (Traag et al., 2019, pp. 4–5). The R packages “leidenalg” and “igraph” implements the Leiden algorithm for partitioning a graph into groups (R Core Team, 2019).

**Identifying focal officers in the network**

An individualized measure of *network capital*, derived from Schwartz and Rouselle (2009), is used to identify focal officers within the use of force co-involvement network. While Borgatti (2006) put forth an efficient approach to identify key actors in a network, his method focused heavily on node-level measures such as centrality, fragmentation, and reach, overemphasizing the positional importance of actors in the network and ignoring their attributes. Schwartz & Rouselle (2009) build on Borgatti’s (2006) approach but expand upon it to incorporate attribute and link weights.

Network capital has been used to identify key websites in online exploitation networks (Westlake, Bouchard and Frank, 2011), compare disruption strategies that are most effective for dismantling a criminal network (Bright et al., 2013, 2015), and prioritize police targets embedded in a broader social network of family, friends, criminal and non-criminal associates (Hashimi & Bouchard, 2017). The overarching goal of employing a measure of network capital is to identify potentially high-risk officers from the larger network. Following the works of Schwartz and Rouselle (2009), Westlake, Bouchard, and Frank (2011), and Hashimi and Bouchard (2016), network capital is modified as:

\[
\text{Network Capital: } \frac{\text{Severity} + \text{Connectivity}}{N + [N(N - 1) \text{ RSL}]}
\]
Where N is the total number of officers in the largest connected component. The resource sharing level (RSL) indicates the percentage of resources that officers make available to others in the network. The RSL can vary between 0 and 1.0. While Schwartz and Rouselle (2009) do not suggest a particular measure for RSL, they propose generating a series of share levels through “thought experiments” to determine optimal levels (p. 196). Provided that officers have minimal to no restrictions on their capacity to communicate or share with one other, the RSL is kept constant (1.0). In other circumstances, the RSL should be adjusted to reflect the importance of network connections within a given network.

*Officer severity* is a count of force incidents (i.e., force reports) per officer. That is the count of force incidents each officer was involved in from 2012 to 2016. This measure is consistent with prior research focusing on how certain “types” of officers are more (or less) likely to engage in the use of force (Worden, 1990, 1995). As commonly found in research on offender versatility (see Guerette et al., 2005), “types” of officers responsible for greater use of force incidents may potentially be liable for excessive use of force incidents as well as problematic behaviors, more broadly (see Worden, 1990; Brandl & Stroshine, 2013). The number of force reports is standardized against the highest-scoring officer (i.e., the officer with the highest number of force reports) within the network. For example, the officer with the highest number of force reports, relative to others, receives a severity score of 1.0. All other officers in the network receive a severity score ranging from 0.0 to 1.0.

*Officer connectivity* is derived from three centrality measures: normalized degree centrality, normalized betweenness centrality, and normalized closeness centrality. *Degree centrality* measures the number of direct contacts (ties) an officer has. Here, it is the count
of partners that an officer has used force from 2012 to 2016. *Betweenness centrality* measures indirect connectivity. It counts the number of times an officer lies on the shortest (geodesic) path between all other officers in a network (Freeman, 1977). Betweenness identifies officers with a “broker-like” position, such that they connect (i.e., through use of force) officers who otherwise would not be connected in the network and have the greatest number of “paths” that go through them (Everton, 2012; Hanneman & Riddle, 2005). Though the degree and betweenness centrality interact with one another, they signify different network roles (Morselli, 2010). Those with high *degree centrality* are visible and tend to be in the “thick of things” (Borgatti, 2006). In this network, these officers use force with many different partners. Those with *high betweenness centrality* are strategically placed (Borgatti, 2006; Morselli, 2010; Zhao & Papachristos, 2020). These officers can control and organize potentially problematic partnerships (i.e., co-involvement in force) between individual officers or groups of officers in the network (Borgatti, 2006; Morselli, 2010).

Finally, *closeness centrality* captures how close (in terms of shortest path distance – i.e., geodesic distance) each officer is to others in the network. To measure officer connectivity, normalized degree centrality, normalized betweenness centrality, and normalized closeness centrality are summated with each officer’s score standardized against the highest-scoring officer. Officers most embedded in the network, relative to all others, receive a connectivity score of 1.0. All other officers in the network receiving a connectivity score ranging from 0.0 to 1.0.
Results

Community-level analysis

Groups delineated from the Leiden algorithm represent “local” working relationships (e.g., peers’ officers use force with) and “peripheral” working relationships (e.g., officers that have used force but not together) embedded within the broader network structure. Groups were delineated from the largest connected component of the use of force network, including 2793 officers with no missing data on key variables. The Leiden community detection algorithm partitioned the network into 56 distinct groups with a modularity score of 0.91. However, because the analysis requires an element of collective group behavior, 25 communities with two or fewer officers were removed, leading to a final sample of 2760 officers nested within 31 Leiden communities. Figure 15 visualizes the structure of each group, with the polygon denoting group boundaries. Appendix 8 defines the attributes and measures used to describe the profile of each group.

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13 For a descriptive summary of the component, please see Table 2 in study 1.
Note. Node colors represent Leiden community membership, where polygon boundaries define the community. Node size weighted by the officer’s measure of network capital \((n \text{ groups} = 31 \text{ groups}; n \text{ officers} = 2760)\), and ties represent co-involvement in a use of force incident.

**Figure 15. Leiden community structure**

Table 8 summarizes the structure and composition of the 31 groups by the attributes of their members. On average, groups have 89 officers \((\text{SD} = 88.63)\), with group sizes that range from five to 400 members. A measure of density indicates that of the officers using force in a group, most are not using force together. Overall, groups are not particularly dense with, on average, a density of 0.11 \((\text{out of a possible} 1.0)\); however, some groups are much denser than others. For example, eight groups scored above the mean density of 0.11, and one department had a density of 0.50, indicating that of all the possible ties in the group, 50% were actualized among officers. Relatedly, most groups are delineated by a single department, suggesting that members of each group, for the most part, are employed in the same department. Indeed, in 65% \((n=20)\) of groups, all members are of the same
department; 35% (n=11) of groups housed members from two or more departments, with one group home to members of four different departments.

To understand the composition of each group, the attributes of their members are also summarized in Table 8. Most groups are predominantly male (94%) and White (84%), with, on average, members self-reporting nine years on the job (SD = 2.08). On average, groups had two officers move (SD = 2.85), such that they filed force reports in two departments across the five years.

Turning to network capital at the aggregate level, the severity of groups tends to be higher than their connectivity, with a severity score of 0.08 (SD = 0.03) of the possible 1.0. Groups accumulated an average of 517 force reports, with a force strength of five (SD = 1.67), across the five years. On average, the connectivity of these groups, including degree, betweenness, and closeness centrality, is 0.02 (SD = 0.01) of the possible 1.0. Across the 31 groups collectively, network capital ranges from 0.03 to 0.14, with an average of 0.09 (SD = 0.03).

Lastly, Appendix 9 provides Pearson’s r correlation matrix, where measures are captured at the group level. While we have to be relatively cautious in over-interpreting bivariate associations, they offer insightful context for understanding the structure and composition of groups and their contribution to network capital.
Table 8. Descriptive summary, community-level (n=31)

<table>
<thead>
<tr>
<th></th>
<th>n</th>
<th>Mean / %</th>
<th>Std. Dev.</th>
<th>Min, Max</th>
<th>25th</th>
<th>75th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size (i.e., number of unique officers)</td>
<td>31</td>
<td>89.03</td>
<td>88.63</td>
<td>5.00</td>
<td>400</td>
<td>43</td>
</tr>
<tr>
<td>Density</td>
<td>31</td>
<td>0.11</td>
<td>0.10</td>
<td>0.02</td>
<td>0.5</td>
<td>0.05</td>
</tr>
<tr>
<td>Departments</td>
<td>31</td>
<td>1.45</td>
<td>0.72</td>
<td>1.00</td>
<td>4.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Sex</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>31</td>
<td>0.94</td>
<td>0.05</td>
<td>0.77</td>
<td>1</td>
<td>0.91</td>
</tr>
<tr>
<td>Female</td>
<td>31</td>
<td>0.06</td>
<td>0.05</td>
<td>0.00</td>
<td>0.23</td>
<td>0.02</td>
</tr>
<tr>
<td>Race/ Ethnicity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>31</td>
<td>0.84</td>
<td>0.19</td>
<td>0.19</td>
<td>1</td>
<td>0.74</td>
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<tr>
<td>Black</td>
<td>31</td>
<td>0.08</td>
<td>0.15</td>
<td>0.00</td>
<td>0.81</td>
<td>0.01</td>
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<td>Hispanic</td>
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<td>0.07</td>
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<td>0.00</td>
<td>0.42</td>
<td>0.00</td>
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<tr>
<td>Experience/ Tenure (years)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Officer Movement</td>
<td>31</td>
<td>1.97</td>
<td>2.85</td>
<td>0.00</td>
<td>16.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Force Reports</td>
<td>31</td>
<td>517.06</td>
<td>656.27</td>
<td>10</td>
<td>2766</td>
<td>171</td>
</tr>
<tr>
<td>Force Strength</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Network Capital</td>
<td>31</td>
<td>4.99</td>
<td>1.67</td>
<td>2.00</td>
<td>8.57</td>
<td>3.96</td>
</tr>
<tr>
<td>Connectivity</td>
<td>31</td>
<td>0.09</td>
<td>0.03</td>
<td>0.03</td>
<td>0.14</td>
<td>0.07</td>
</tr>
<tr>
<td>Severity</td>
<td>31</td>
<td>0.02</td>
<td>0.01</td>
<td>0.00</td>
<td>0.05</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Note.  
1“Force Strength” indicates the number of force reports per group, divided by the size of the group.  
ABBREVIATIONS. SD = Standard Deviation.

Prioritizing groups

Appendix 10 breaks down the structure and composition of each group (n=31). Groups are then ranked by their aggregate measure of network capital. Thus, if the intervention focuses on groups of officers (and most logically, departments) that contribute most to the overall network capital, ranking these groups is an important first step. For example, the mean aggregate network capital across all groups is 0.09; if we were to consider groups that score above the mean, we isolate 13 focal groups. However, one standard deviation from the mean, with a network capital score of 0.12, would allow us to isolate, and hone on, five focal groups: Group 2(Atlantic City, Atlantic County), Group 6(Elizabeth, Union County), Group 1(Camden City, Camden County), Group 19(Voorhees, Camden County), Group
4(Toms River, Ocean County). These groups are labeled in Figure 16, and a summary of the structure and composition of the “Focal 5” is in Table 9.

Note. Node colors represent Leiden community membership, where polygon boundaries define the community. Node size weighted by the officer’s measure of network capital ($n$ groups = 31 groups; $n$ officers = 2760), and ties represent co-involvement in a use of force incident.

**Figure 16. “Focal 5” Groups**

Looking down the columns for each “Focal 5” group provides quick insight into their composition. For example, the two groups that contribute the most network capital, Atlantic City, Atlantic County (Group 2), and Elizabeth, Elizabeth County (Group 4), are not necessarily the largest, nor have the highest density or highest number of force reports. However, as indicated by their network capital score, Group 2 and Group 6 house members that jointly use force with more frequency (i.e., severity) and have the widest network reach (i.e., connectivity).
Tending to other group characteristics, in Toms River, Ocean County (Group 4), 97% of force reports were by males. In contrast, Elizabeth, Union County (Group 6), relative to the other four groups, is one of the most racially/ethnically diverse groups in force usage. Of all the officers reporting force in Group 6, 51% are White, 7% are Black, and 42% are Hispanic.

Officers that reported force in Camden City, Camden County (Group 1), were, on average, the second least experienced with a reported five years in the force. Likewise, it houses a relatively high proportion of officers that have reported force in multiple departments (4%) relative to other groups. Finally, Voorhees, Camden County (Group 19) is the smallest of the five with 54 officers who reported 311 instances of force. However, it is somewhat interconnected, with a density that is three times as high as the other focal groups and, on average, houses the highest proportion of officers that have reported force in multiple departments (6%) relative to other groups.
Table 9. Characteristics of the “Focal 5” groups, means, and proportions

<table>
<thead>
<tr>
<th></th>
<th>Group 2</th>
<th>Group 6</th>
<th>Group 1</th>
<th>Group 19</th>
<th>Group 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rank</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>n Size</td>
<td>308</td>
<td>146</td>
<td>400</td>
<td>54</td>
<td>190</td>
</tr>
<tr>
<td>n Ties</td>
<td>1330</td>
<td>420</td>
<td>1301</td>
<td>173</td>
<td>751</td>
</tr>
<tr>
<td>Density</td>
<td>0.03</td>
<td>0.04</td>
<td>0.02</td>
<td>0.12</td>
<td>0.04</td>
</tr>
<tr>
<td>% Sex</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>90</td>
<td>91</td>
<td>93</td>
<td>94</td>
<td>97</td>
</tr>
<tr>
<td>Female</td>
<td>10</td>
<td>9</td>
<td>7</td>
<td>6</td>
<td>3</td>
</tr>
<tr>
<td>% Race/Ethnicity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>74</td>
<td>51</td>
<td>65</td>
<td>91</td>
<td>97</td>
</tr>
<tr>
<td>Black</td>
<td>17</td>
<td>7</td>
<td>15</td>
<td>6</td>
<td>1</td>
</tr>
<tr>
<td>Hispanic</td>
<td>9</td>
<td>42</td>
<td>20</td>
<td>4</td>
<td>3</td>
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<tr>
<td>Avg. Experience</td>
<td>9.38</td>
<td>8.82</td>
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<td>9.00</td>
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<td>n Departments</td>
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<td>1</td>
<td>2</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Officer Movement</td>
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<td>0.68</td>
<td>4.00</td>
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<td>n Force Reports</td>
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<td>1251</td>
<td>2766</td>
<td>311</td>
<td>1175</td>
</tr>
<tr>
<td>Avg. Force</td>
<td>8.37</td>
<td>8.57</td>
<td>6.92</td>
<td>5.76</td>
<td>6.28</td>
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<tr>
<td>Strength</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. Network</td>
<td>0.14</td>
<td>0.14</td>
<td>0.12</td>
<td>0.12</td>
<td>0.12</td>
</tr>
<tr>
<td>Capital</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Main Department</td>
<td>Atlantic City</td>
<td>Elizabeth</td>
<td>Camden</td>
<td>Voorhees</td>
<td>Toms River</td>
</tr>
</tbody>
</table>

Note.  
1 Percentage of officers, relative to the size of the group, that have reported force in more than one department across the five years

Officer-level analysis

Moving from the group-level to officer-levels redirects focus from an aggregate intervention approach to nodes of officers. The network comprises 2,760 officers with a mean network capital of 0.10 (SD = 0.11). Across the 2,760 officers, network capital ranges from 0.02 to 1.0. For example, officers who score a 0.02 on network capital are jointly the least connected and least severe in using force, relative to all other officers in the network. In contrast, officers who score a 1 are jointly the most connected and use the highest frequency of force, relative to all other officers in the network. Appendix 11 provides a summary of the various measures that make up network capital.
Figure 17 provides Pearson’s r correlation matrix, where measures are captured at the officer-level. While bivariate results have to be interpreted with some level of caution, network capital, as expected, is positively associated with the severity ($r=0.90$, $p<0.05$) and connectivity ($r=0.64$, $p<0.05$) of an officer. In contrast, the association between connectivity and severity is relatively small in magnitude ($r=0.25$, $p<0.05$). Likewise, network capital is positively associated with the size of the officer’s groups ($r=0.14$, $p<0.05$), the number of ties within the group ($r=0.17$, $p<0.05$), but negatively associated with the overall interconnectedness (i.e., density) of the group ($r=-0.10$, $p<0.05$). Finally, there is a positive association between network capital and male officers ($r=0.09$, $p<0.05$), the number of force reports officers filed across multiple departments ($r=0.18$, $p<0.05$), and a negative association between network capital and officer years of experience ($r=-0.12$, $p<0.05$).
Note. The map shows correlation coefficients for all pairs of variables (with deeper colors representing stronger correlations). Correlations not significantly different from 0 are in white. \[p<0.05\]

**Figure 17. Pearson’s r correlation matrix at the officer-level (n=2,760)**

**Prioritizing officers**

The next feasible step is to identify focal officers with high-risk profiles relative to their colleagues. There are many appropriate methods for this, such as using the mean or the standard deviation from the mean. For example, of the 2760 officers in the network, about 32% (n=872) of officers score above the mean network capital of 0.11. However, because this approach tends to be wide-net, it may not be practically feasible if the goal is to intervene. Thus, another common approach is to identify outliers, and in this case, “focal officers,” by using standard deviations. Figure 18 provides a visual representation of the cluster of officers that could be isolated using three baselines. These officers are
highlighted in blue: +1 standard deviation above the mean network capital (network capital=0.21; n officers=315), +2 standard deviations above the mean network capital (network capital=0.31; n officers=135), and +3 standard deviation above the mean network capital (network capital=0.42; n officers=60).

Note. The area shaded in gray represents the group of officers that fall within the boundaries.

**Figure 18. Identifying the “net” of focal officers**

Table 10 categorizes these officers into low-risk, mid-risk, and peak-risk and summarizes their characteristics. Of the 2760 officers in the network, 11% are low-risk, 5% are mid-risk, and 2% are peak-risk. Collectively, most focal officers are male and White. Officers in the mid-risk category are, on average, the oldest. In contrast, officers in the high-risk category are, on average, the youngest. Focal officers ranging from lowest to highest risk have filed, on average, 18 to 27 force reports across the five years. When
considering their combined degree, betweenness, and closeness centrality, these officers are relatively well connected in the network (0.09-0.22). Take, for example, their reach, which considers the number of unique ties they have in the network. The 315 officers in the low-risk category have direct ties to, such that they can “reach,” 28% of the use of force network. Similarly, officers in the mid-risk group can reach 15% of the network, and officers in the peak-risk category can reach approximately 8% of the network.

| Table 10. Focal officers by risk categories |
|-------------------------------|---------------------------------|------------------|
|                              | Low-Risk (+1 SD) | Mid-Risk (+2 SD) | Peak-Risk (+3 SD) |
| Network Capital threshold    | 0.21             | 0.31             | 0.42             |
| n Focal Officers             | 315              | 135              | 60               |
| % Officers in the Network    | 11.41            | 4.89             | 2.17             |
| % Reach (degree centrality)  | 27.82            | 14.61            | 7.58             |
| Avg. Force Reports           | 18.00            | 23.00            | 27.00            |
| Avg. Connectivity            | 0.09             | 0.14             | 0.22             |
| % Male                       | 98.00            | 98.00            | 97.00            |
| % White                      | 73.00            | 73.00            | 65.00            |
| % Black                      | 9.00             | 11.00            | 13.00            |
| % Hispanic                   | 18.00            | 16.00            | 22.00            |
| Avg. Experience/ Tenure      | 6.55             | 9.06             | 4.16             |
| % Department moves           | 7.30             | 11.85            | 13.33            |
| Groups (i.e., Leiden Community) | 24.00          | 22.00            | 12.00            |

ABBREVIATIONS. SD = Standard Deviation.

Honing on officer location and movement, officers in the low-risk category stem from 24 (of the possible 31) Leiden groups, with 7% of officers having filed force reports in multiple departments. Officers in the mid-risk stem from 22 (of the possible 31) Leiden groups, with approximately 12% of officers filing force reports in multiple departments. Officers in the peak-risk category stem from 12 (of the possible 31) Leiden groups, with 13% of officers filing force reports in multiple departments.
Disaggregating high-risk officers by their membership in the “Focal 5” groups, Table 11 shows that, relative to the group’s size, most officers at peak-risk are in Group 19. In contrast, most officers at mid-risk and low-risk are in Group 2.

| Table 11. Low, mid, and peak risk officers by group membership, proportions |
|-----------------------------|---------------|-------------|---------------|-------------|---------------|
|                             | Group 2       | Group 6     | Group 1       | Group 19     | Group 4       |
| % Low-Risk                  | 20.8          | 19.9        | 15.3          | 14.8         | 15.3          |
| % Mid-Risk                  | 12.3          | 10.3        | 6.3           | 11.1         | 7.9           |
| % Peak-Risk                 | 5.8           | 6.2         | 3.3           | 7.4          | 3.2           |

Note. 1 The percentage of officers, relative to the group's overall size as indicated in Table 10, at low-risk, med-risk, and peak-risk.

If we were to intervene on officers strictly in the peak-risk category, 83% of the 60 officers (n=50) are embedded in the “Focal 5” group: 18 officers are members of Group 2 (Atlantic City), 13 officers are members of group 1 (Camden), nine officers are members of group 6 (Elizabeth), six officers are members of Group 4 (Toms River) and four officers are members of Group 19 (Voorhees).

**Discussion**

Terrill and Mastrofski (2002) argued that “because most efforts to control police discretion in the use of force are focused on selecting and molding individual practitioners, it matters a great deal whether some officers are more coercive than others” (p. 218). Similarly, a growing body of research has acknowledged that a small percentage of officers are responsible for a disproportionate share of complaints and problematic behaviors in any police department.

Indeed, while current systems are in place to deal with such officers, they tend to be reactive, responding to problematic officers only after such behaviors warrant formal disciplinary action. For example, an early warning system is a data-based police management tool designed to select, intervene, and monitor officers whose behaviors are
deemed problematic. With the early warning system, behaviors such as “citizen complaints, firearm-discharge and force reports, civil litigation, resisting-arrest incidents, and high-speed pursuits and vehicular damage” are used to flag problematic officers (Walker et al., 2001, p. 2). Officers “flagged” are provided with counseling or training to correct their behaviors. These officers are monitored on a case-by-case approach for subsequent performance issues. However, there are three issues with this approach. First, there are no definite standards or methods to select which officers participate in the early warning system. Second, not all agencies subscribe to an effective system. They are considered “high-maintenance” systems that require time, investments, and administrative resources (Alpert & Walker, 2000). Third, there are inconsistencies in what indicators should be flagged. For example, most civilian complaints are unfounded. They raise questions about the civilians’ perception, bias, and interpretation of what is lawful, appropriate, and requires a review versus what gets reviewed (Levin & Thomas, 1997; Mourtgos & Adams, 2019; Pate et al., 1993).

Network capital builds on these limitations. By capitalizing on the department's data, it combines the severity of the acting officer’s behavior and uses three network measures (degree, betweenness, closeness) to capitalize on the structural position of high-risk or groups of high-risk officers. Network capital identifies officers that may benefit the most from prevention and crime control strategies (Alpert & Walker, 2000; Walker, 2001) and provides a means to intervene before such behaviors are worsened and diffused across the department (Chappell & Piquero, 2004; Cooper, 2012; Crank et al., 2007). With network capital, two selection methods are put forth, the group-based and individual-based
approach, as a means to distinguish a select group of high-risk officers from other similarly situated peers.

The group-based approach challenges the individualistic “bad apple” approach. It adopts the “bad barrels” approach by relaying attention to systematic change at the aggregate level. Focusing on groups of officers may allow us to evaluate how the group may permeate a culture that considers force to be an acceptable means of conflict management and potentially mobilize larger structural change in departments' occupational and organizational makeup. More specifically, we tackle the “peer element” of police work, which shapes “appropriate methods for handling situations, cues to be considered when taking control, and the levels of coercion that are appropriate to use” (McCluskey et al., 2005, p. 22; also see Hunt 1985).

With the adoption of the group-based approach, 2,760 officers were nested within 31 groups identified by the Leiden algorithm. Of the 31 groups, five groups (i.e., Focal 5) were selected based on their aggregate network capital measure. These five groups comprise 40% of the network. Although there were variations across the structure and composition of groups, most groups were primarily White and male. Overall, 49% of all ties in the largest connected component concentrate on these five groups, with Group 2 comprising almost 17% of all network ties. Additionally, as shown in Figure 16, four of the five groups connect, such that members cross group boundaries (i.e., officers who have used force with officers from other groups). These officers have the potential to mediate the flow of behaviors between groups who otherwise would have no direct ties.

Turning to intervention or prevention strategies that could be implemented to mobilize occupational and cultural change at the group-level, there should be some
reflexivity. Indeed, strategies need to be tailored to the department’s aims, needs, and operational capacity, with some strategies proving to be more effective for some departments than others. For example, de-escalation techniques are a set of intervention strategies that train officers on 1) the importance of maintaining personal control and appearing calm in hostile situations (Delaney & Johnson, 2006; Duperouzel, 2008), 2) using verbal and negotiation skills through active listening, appropriate body language (Carlsson et al., 2000; Johnson & Hauser, 2001), and 3) the importance of fostering mutuality, rapport, and empathy to eliminate the need for aggression when they are on the street (Carlsson et al., 2000; Todak & James, 2018). It assumes that when officers are equipped with such skills, they are poised to interact with civilians effectively and safely, especially when an arrest is forthcoming (Todak & James, 2018). Additionally, such exchanges foster legitimacy as they demonstrate neutral policing and generate more respectful interactions with civilians (Todak & James, 2018).

De-escalation training is integrated within the training policies of many departments. As such, most training tends to be leveraged to the department as a whole. For example, Goh (in press) found a drop in serious uses of force after de-escalation training took place in a department. The effects of the de-escalation training on serious force were significant, with a decline in serious force incidents by approximately 40% post-intervention period (p. 19). Likewise, a report by Engel and colleagues (2020) found that de-escalation training for the Louisville Metro Police Department was associated with a 28.1% reduction in use of force, 26.3% reduction in civilian injury, and 36.0% reduction in officer injuries (p. 80). However, this is not to conclude that the effects of de-escalation training are widespread and result in positive changes for every department. In fact, in their
systematic review of 64 de-escalation training evaluations over the last 40 years, Engel et al. (2020) found weak evidence supporting the long-term effects of de-escalation training. Though their evaluation focused on de-escalation programs in the fields of nursing and psychiatry, they did underline few adverse effects of de-escalation, underlining its value in training officers to respond to “incidents of crisis, aggression, or violence” (Engel, McManus, et al., 2020, p. 740)

Alternatively, intervention or prevention strategies geared towards uncovering whether there is something systemic and fundamentally problematic in police attitudes, identities, and conduct at the group-level can also be mobilized. McLean et al. (2020) found that social interaction training, wherein police officers in two departments were trained on “decision-making, de-escalation, empathy, rapport building, and self-control,” had a significant effect on officers’ procedural justice priorities and behaviors (p. 809). Social interaction training improved officers’ attitudes, for example, their ability to maintain self-control and de-prioritize the use of physical force, with treated officers placing a higher priority on communication tactics that were procedurally fair in officer–civilian encounters. Specifically, these tactics provided an avenue to understand why and how officers differ in their communication skills and civilian interactions from their peers of similar occupational status and, more broadly, from the general population. It also allowed officers to have ownership and accountability of the training program as trainers were from the police departments themselves.

Because limited time and resources may make it unrealistic to intervene on whole departments and “treat” every officer, the second selection method is individualistic. Inspired by the “focused deterrence approaches,” it concentrates on individual officers who
are problematic or exhibit risks of future problematic behaviors relative to their colleagues. These officers are key to the network as they jointly: 1) use force the most, 2) use force with many others, and 3) are in a structural position where they are likely to influence others and thus, have the potential to exacerbate problematic behaviors through the department or to mobilize change (Valente, 2012; Wheeler et al., 2019).

Strictly looking at the placement of the nodes in Figure 19, those high in network capital, as indicated by the size of the node, tend to cluster and are drawn to the core of the network. This was verified with the Leiden Algorithm. Approximately seven percent of officers, who measured at least one standard deviation above the mean network capital in the network, were members of the “Focal 5”. Ultimately, using network capital as a method to identify focal officers led to three baseline estimates: 11% of officers in the use of force network were identified as low-risk, five percent as mid-risk, and two percent as peak-risk.

While these officers represent a small proportion of the use of force network, officers in the low-risk category are responsible for 35% of all force incidents and reach approximately 28% of officers in the largest connected component network; officers in the mid-risk category are responsible for 19% of all force incidents and reach approximately 15% of officers in the largest connected component network; officers in the peak-risk categories are responsible for 10% of all force incidents and reach approximately 8% of officers in the largest connected component network. These officers may benefit the most from intervention strategies as they, in comparison to their colleagues, are more likely to be: 1) unqualified in using “persuasion” and “negotiation” tactics that are crucial to their

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14 Of the 2760 officers in network, 315 officers scored +1 SD above the mean network capital. Of the 315 officers, 191 were members of the “Focal 5”
role as peacemakers and are likely to resort to force too quickly (Muir, 1977) and 2) overly productive, such that they fail to adopt an appropriate exit strategy (e.g., comforting civilians or satisfying civilians requests) that does not resort to force, and thus escalate the likelihood of physical confrontation (Terrill and McCluskey, 2002).

Figure 19. The structural position of officers that are high in network capital, relative to other officers (node size = network capital)

When it comes to addressing “key actors” in a network, a possibility in criminal and non-criminal networks is to remove key actors from the equation either through arrests or, in the case of officers, by terminating or re-locating them to other departments. However, “removing” problematic officers, for example, officers who generate a substantial percentage of complaints, is relatively difficult, especially in cases where police unions are involved. Also, the overall effects of removals may be negligible. For example, using civilian complaint data filed against officers in the CPD from 2012 to 2017, Chaflin and Kaplan (2020) found that removing high-risk officers does not lead to “large-scale
reductions” in complaints. Their policy simulation estimated that removing the top two percent of officers, based on the number of complaints they generated, would have reduced 0.8 to 1.2 percent of force complaints. Removing the top 10% of officers, based on the number of complaints they generated, would have reduced 4.9 to 6.3 percent of force complaints (Chaflin & Kaplan, 2020). They concluded that incapacitating the bad apples “is unlikely to lead to a large reduction in use of force complaints, absent appreciable deterrence or spillover effects or broader cultural change” (p. 4).

Rather, to demonstrate the efficacy of “focused deterrence” approaches that select on key individuals, or small groups of individuals, with the aims of getting the deterrence message out to the broader network (e.g., spillover effect), Wheeler et al. (2019) developed an algorithm that relied solely upon network position. Focusing on gang-involved individuals, they found that 24 of the individuals selected for call-ins had ties to 75% of the corresponding gang network in one of the cities. However, if they were to select 26 key individuals in a connected component, they could reach the entire network. Together, both studies call on the importance of not only identifying and intervening on individuals (e.g., officers, gang members, etc.) based on their behaviors, but also based on their location in the network, given that any action taken against one individual has the potential to exert social pressure on those they interact with.

An effective and immediate measure for dealing with focal officers may be in the form of increased monitoring and dialogue (i.e., calling in officers and conducting face-to-face meetings), warnings, and reassignments. For example, to reduce the likelihood of being involved in problematic behaviors and exacerbating these behaviors through the department, focal officers may benefit the most from warnings and reassignments. Access
to this type of information is useful for upper management and supervisors in making selection decisions, such as assigning officers to particular neighborhoods and patrol areas, partnerships, or evaluating the suitability of select officers to carry out particular duties (i.e., promotions). Indeed, at an operational level, supervisors can shuffle officer partnerships, such as identifying officers high on network capital and partnering them with officers low on network capital but equally or more experienced. Supervisors should also be mindful of the characteristics of such partnerships, preventing partnerships that may attract more significant disapproval from civilians. For example, Levin and Thomas (1997) found that arresting officers’ racial identity (i.e., whether both arresting officers were White, Black, or Black and White) impacted how their actions and behaviors were perceived by civilians observing the incident. Their finds suggested that civilians perceived “significantly greater violence and illegality” when arresting officers were both White than when both arresting officers were Black, or Black and White (p. 582).

Long-term intervention and prevention training procedures that encourage non-enforcement and positive interactions with the public may also be an effective means to correct individualized behaviors (Rahr & Rice, 2015; Stoughton, 2014; Police Executive Research Forum, 2015; President’s Task Force on 21st Century Policing, 2015; Wood et al., 2020). For example, in an evaluation of a procedural justice training program led by the CPD, Wood et al. (2020) concluded that procedural justice training has the potential to change police behaviors. The procedural justice program focused on improving civilian-officer relations and officer decision-making skills by stressing the “importance of voice, neutrality, respect, and trustworthiness in policing actions” (p. 9815). Specifically, it emphasized objective dialogue by training officers to approach, listen, and respond to
civilian concerns in a way that was respectful and minimized conflict. It also encouraged officers to mobilize non-forceful behaviors. While only select officers were identified to participate in the training program, Wood et al. (2020) found that procedural justice training effectively reduced the use of serious force (i.e., weapon-related) by trained officers.

Collectively, individual and group-based strategies have shown relative success in mobilizing change in officers’ behaviors. A measure such as network capital systematizes the selection process, and thus, the efficacy of these programs, overall. Indeed, departments will not only be able to systematically identify which officers require attention, but they can mobilize officer networks by concentrating their resources on those most in need and those most likely to exacerbate problematic behaviors and influence colleagues (Brandl & Stroshine, 2013; Ouellet et al., 2019; Terrill & Mastrofski, 2002; Wood et al., 2019; Worden, 1990).

**Key challenges and Implications**

Network capital – whether it is applied to identify departments, groups, or individual officers – is designed as a systematic method to identify patterns of behaviors. It can be used as a selection criterion for current systems, such as early warning systems or intervention, prevention, and control programs mentioned above. However, the study does come with some limitations. First, there is their underlying assumption of a diffusion effect that is not measured in this study. It is reasonable to assume that some officers will not reach some network segments, whereas others will relay deterrence effects. While outside of the current study, this approach should be tested and compared with simulation methods (Chaflin & Kaplan, 2020), algorithmic approaches (Wheeler et al., 2019), or synthetic
control procedures (Goh, in press) that can test the effect of various types of interventions as well as the potential for any contagion effects. Second, while officers generally show persistence in generating complaints and use of force across their careers (Chaflin & Kaplan, 2020), this data was only available from 2012 through 2016, thus censored. The next feasible step would be to break this analysis down further and track use of force across officers' career trajectories over a longer period of time.

Third, while the frequency of force was used as an indicator of severity, this is only one of many potentially useful indicators. The most helpful scenario would be to use weights to integrate various measures such as force reports with substantiated and unstained civilian complaints, history of misconduct, and internal or external disciple records to see if officers high on these indicators concentrate and where they are situated overall. It might also be useful to incorporate relevant officer attributes or situational and organizational indicators tailored to the needs to problems of the department understudy. Indeed, network capital is malleable, and the measure demonstrated in the current study is just one method. Network capital can and should be modified to meet the operational capacities of departments and overall needs.

Lastly, it stands that use of force incidents only represent part of the picture. Officers have the authority to use or threaten to use force to carry out their duties, enforce the law, and protect the public (Bittner, 1970). While most do so without generating a significant number of excessive force or deadly force reports, it may be the case that some officers are continuously deployed to problematic areas and thus have to turn to force more than their counterparts. Simultaneously, some officers might be overly active and in units that place them in situations where they have to use force as a means of protection. While
network capital is designed to hone on focal officers, regardless of individual, organizational, and situational characteristics, there needs to be a larger discussion on why some departments, officers, or groups of officers, generate more force than similarly situated peers, as well steps to mediate such effects. For example, suppose force is an outcome of the environment. In that case, interventions should be placed on whole departments. Alternatively, if force is concentrated on select officers, interventions should be placed on individual officers or partnerships. Though it remains that force is a legitimate option, officers must do so as a final resort for ensuring public safety (Fyfe, 1979; Klockars, 1996). This is not only echoed by Bitter (1970), who stated that when it comes to using force, a defining “skill of policing consists of finding ways to avoid its use” (p. 40), but it is also stressed in the Attorney General’s policy guidelines.
CONCLUSION AND MOVING FORWARD

Unlike conventional studies of police behavior that focus exclusively on situational, organizational, or officer-level predictors of force, this study focuses on social processes drawing on networks to explain use of force behaviors. In between officer-level predictors of force and organizational predictors of force are officer networks that arise from a set of interactions in which police socialization occurs, and norms and behaviors are learned, neutralized, and reinforced. Network analysis allows for the visual and analytical understanding of the social and structural makeup of organizations. It provides insight into the interconnectedness of a group(s), indicates who is tied to who, identifies focal nodes, and delineates group boundaries in the network.

By highlighting police behaviors in a way that parallels research on how crime and deviance is a grouped phenomenon, this dissertation provides an alternative starting point for understanding how individual, dyadic, contextual, and network processes are associated with police uses of force. The first study evaluates police partnerships, finding that force is concentrated on select officers and partnerships. Much like other forms of co-offending behaviors, results suggest that homophily with respect to race and experience is associated with a higher probability of using force together. Network processes further contribute to such behaviors, with officers likely to use force with shared partners. Yet, despite increased awareness of the collective nature of force, few studies have focused on how organizational and environmental determinants introduce specialization or variations in the degree and types of force employed in departments. The second study, as such, focuses on broader patterns of applications of force. While it finds a considerable degree of specialization in patterns of use of force behaviors across the five years, with most departments relying on
force that is traditionally categorized on the lower end of the spectrum (i.e., the use of physical force), key measures of departmental composition and jurisdictional crime rates are associated with versatility in the types, and thus degrees, of force employed.

The last study capitalizes on findings from Study 1 that force is centralized on select officers and prior calls that attribute a significant proportion of problematic behaviors to a small proportion of officers. Indeed, use of force, when employed appropriately, is not akin to crime or deviance. However, it becomes problematic when officers resort to force frequently and demonstrate select and typical patterns of using force with colleagues in proximate social and spatial space (Brown, 1988; Skolnick & Fyfe, 1993). As such, the implications of this study are relatively straightforward; if a department or agency wants to address issues pertaining to use of force, they must focus on both the behavior of officers as well as pay attention to their structural position in the network. A measure such as network capital systematizes the selection process; it can be modified to reflect the operational capacities and individualized needs of departments and increase the efficacy of programs. Through network capital, 11% of officers (i.e., bad apples) and five groups (i.e., bad barrels) in the largest connected component were identified as high-risk, making them a particularly effective and efficient starting point for intervention and prevention purposes. Indeed, departments can mobilize the relationships between officers and customize their responses to activate behavioral shifts at the individual-level or the group level.

While the study provides several methodological insights proving to be a step forward in understanding the social processes that generate police use of force, a few broader issues should be noted. First and foremost, the consistency, validity, and quality of data rely on several key factors. Namely, the structural characteristics of a police
department influence the uses of force. Features of the organization and department (e.g., size, resources, organizational aims) attract the types of individuals that select into the profession (e.g., self-selection see Kane & White, 2009), the behavior of individual officers, and how these incidents are reported in official data. While official force reports are the most efficient resources for gathering large amounts of data, especially across multiple departments, they are only as accurate as the officer’s accounts of events (Terrill, 2001).

Use of force is a sensitive topical issue analogous to self-reporting crime and delinquent behaviors (see Junger-Tas & Marshall, 1999; Laumann et al., 1994). Similarly, supervisors and upper management also have a stake in force reports related to the organization. Excessive use of force draws undesirable consequences and increased public scrutiny at the officer level and the department and agency level through civilian complaints, civil lawsuits and has legal ramifications in the form of consent decrees. These reports only reflect the police officer's perspective and understanding of what happened and what led to the event. They rely on the officer’s perspective. As such, officers may report incidents in a way(s) that justifies or minimizes their actions (Laumann et al., 1994; Junger-Tas & Marshall, 1999).

This study uses archival and secondary data and is thus limited in several ways (Eckles & Stradley, 2012; Shadish, 2013). This study is limited in which variables are chosen as controls and how they are employed to fix selection bias or improve data reliability. Though the Force Report is one of the only databases identifying uses of force across a whole state, several key variables at the officer level, department/agency level, and situational/environmental level that impact officer conduct and agency procedures are
omitted. Moreover, variables that indicate whether an officer has previously been involved in misconduct or excessive use of force were not available for this study. As such, we are unable to: 1) predict which factors influence misconduct to any substantial degree (Kane & White, 2009), 2) locate officers involved in misconduct, and 3) determine whether any of their current or previous interactions were deemed as inappropriate, excessive, or if officers were disciplined.

Finally, the scope of the current study is limited to uses of force employed by officers in municipal police departments in New Jersey and the New Jersey State Police from 2012 to 2016, and virtually the laws and regulations under which officers in New Jersey use force and are required to report force by the Attorney General. It does not necessarily represent all force incidents across America or across time, which hinders the findings' external validity. While the Force Report is relatively exhaustive and considered the most comprehensive statewide police force database in the U.S., it still may not be comparable to force incidents in areas outside of New Jersey. This speaks to a broader issue on how agencies elect to record and define “use of force,” which ultimately impacts variations in measurements, reporting practices, and policies and procedures (Alpert & Dunham, 1999; Crawford & Burns, 1998; Engel, 2008; Hickman et al., 2008; Terrill et al., 2012). This variation can lead to sizable differences in the number of incidents where force is reported and what type of force is included in such reports (Hickman et al., 2008).

Findings from all three studies provide actionable information and critical insights for policy, practice, and the implications of police-community relations. Much like any other occupation, individual officers have their own set of strengths and weaknesses. They are likely to select into specific types of relationships and develop some behavioral
tendencies more so than others. However, the interdependent nature of police organizations, and the interdependencies between officers, is especially pertinent given the importance of police culture (Skolnick, 2002; Skolnick, 1966; Westley, 1970), where a preoccupation with the dangers of the profession and the coercive power and authority that police officers have over the public (Bittner, 1970; Manning, 1977; Marenin, 2016; Sierra-Arévalo, 2019; Skolnick, 1966; Van Maanen, 1978; Westley, 1970) cultivates an internal “working personality.” This “working personality” creates a division between law enforcement agencies and the communities they police, particularly in communities of color (Cochran & Bromley, 2003; Kappeler et al., 1998; Reuss-Ianni & Ianni, 1983; Roithmayr, 2016), and impacts officer activities on and off the job (Bennett, 1984; Reuss-Ianni & Ianni, 1983; Rubinstein, 1993; Van Maanen, 1978b).

Thus, police departments may want to pay considerable attention to the makeup of their department by 1) paying greater attention to the skills, behavioral tendencies, strengths, and weaknesses of officers and officer partnerships, 2) focusing on broader patterns of applications of force and lawful (and unlawful) coercive activity in the department, followed by how organizational structure and culture foster these behaviors, and 3) directing and focusing intervention and training programs to reflect findings that use of force is commonly employed by a small group of high-risk officers (Adams et al., 1999; Brandl et al., 2001; Brandl & Stroshine, 2013; Ouellet et al., 2019; Wood et al., 2019).

Departments may also want to pay attention to how personal and vicarious contact with the police, specifically, police use of force, impacts the public’s view of the appropriateness of criminal justice officials and the extent to which legal authorities are
viewed as legitimate (Brandl et al., 1994; Sunshine & Tyler, 2003; Tyler, 1990; Tyler et al., 2014). Research examining the relationship between public perceptions and police contact has found that while positive voluntary interactions demonstrate small effects on civilian attitudes toward the police (Donner et al., 2015; Wells, 2007), negative interactions significantly, and more fervently, impact police perceptions and future offending behaviors (Brunson, 2007; Desmond et al., 2016; Tyler et al., 2014).

Additionally, the experiences of one’s network (e.g., friends, neighbors, and family members) with the police has vicarious effects on the community’s general perceptions of police legitimacy and actions (Tyler, 1990), and more broadly shapes perceptions of the legitimacy of law and legal authorities (Fagan & Tyler, 2005; Piquero et al., 2005), the fairness of police actions (Tyler, 1990) and impacts the likelihood of compliance with legal and social norms (Mazerolle et al., 2013). Indeed, those who are more cynical of the police and legal actors are found to be less likely to comply with the law, have higher delinquency rates (Kirk & Matsuda, 2011; Tyler, 1990), and develop more negative attitudes regarding the justice system over time (Fine et al., 2016), whereas, satisfied consumers of police services likely to comply with police during interactions, accept and express support for the decisions made by the police and law enforcement agencies, and to obey the law (Mazerolle et al., 2013; Tyler & Wakslak, 2004; Walker & Archbold, 2018). Taking the time and the necessary steps - at the government, agency, and officer level - to improve police-civilian relations, as such not only helps police avoid encounters that place them at higher risks of using and succumbing to violence and victimization, but it also builds police legitimacy and increases trust in the communities that are policed.
The future of policing in New Jersey

The Attorney General’s office has shown motive for reviving New Jersey's Use of Force Policy (2000;1985) with updates to its statewide de-escalation training in 2017, implementation of a statewide implicit bias training in 2018, and the Excelling in Policing Initiative in 2019 (New Jersey Attorney General, 2020), however, outrage over several high-profile incidents and greater calls for police reform, transparency, and accountability, finally led to its overhaul (Napoliello & Sullivan, 2020). First, when NJ Advance Media compiled the Force Report, there was no centralized database. However, in 2020 the Attorney General announced that they intend to launch a statewide database of police use of force (i.e., Use of Force Portal) (Napoliello & Sullivan, 2020; New Jersey Attorney General, 2020). This database is part of a pilot program that will track police use of force in selected departments and be implemented statewide shortly afterward. Moreover, New Jersey intends to move from filing paper force reports to an online electric system for filing force reports. The online electric form will be standardized and call for officers to report on over "100 data points" for every incident (Serrano, 2020).

Second, after more than 20 years, the state has announced significant changes to the current policy. Police revisions include additional restrictions on officers' use of less-than-lethal force, vehicular pursuits, and chokeholds. While the policy continues to stress the use of force as a last resort, with officers required by law to deescalate and to intervene if they see a colleague using illegal or excessive use of force (New Jersey Attorney General, 2000), officers will also be required to report when they draw and point their guns as "show of force" (Janoski, 2020). This change ensures that officers only resort to using their firearms when they believe that deadly force is necessary. Along these lines, the Attorney
General has also urged departments to establish an early-warning system and release the names of officers who have been subject to major discipline (Janoski, 2020; Napoliello & Sullivan, 2020). The Attorney General’s Office (2020) is also working to develop a new team of community-relations specialists (i.e., Incident Response Team) under the Division on Civil Rights (DCR) to respond to major incidents such as police shootings.

Finally, in an attempt to improve police-community relations, deescalate challenging incidents, and decrease excessive use of force and death-in-custody incidents, the Attorney General’s office has endorsed a statewide certification training program for police officers to enhance police training (New Jersey Attorney General, 2020). The Attorney General's Office is also “exploring” a "crisis intervention" training program (i.e., CIT training program). This program will train officers to respond to civilians with mental health issues (New Jersey Attorney General, 2020). To gauge the capacity to build a statewide training program, the CIT program will start as a pilot program in Atlantic City, Paterson, Trenton, Millville, and State Police Troopers in Trenton (New Jersey Attorney General, 2020).

Although New Jersey considers itself a leader for police reforms, being the first to implement many changes, these proposals are no small task (Berman, 2020). Indeed, a handful of measures are still underway, under review, or facing backlash from police unions (Robert, 2020). These changes, however, will hopefully continue to shift this movement towards policing that is objective, reasonable, and fair, with the Attorney General stating, “that every law enforcement officer in our state […should be required to] do all they can to protect the life, liberty, and dignity of every resident in every interaction” (Shaw, 2020).
REFERENCES


CNBC. (2016). Philando Castile shot by police in Minnesota, reports say, a day after Alton Sterling shooting. Retrieved from

Chaflin, A., & Kaplan, J. (2020). How many complaints against police officers can be abated by incapacitating a few "Bad Apples"? Available at SSRN: https://ssrn.com/abstract=367398


Furst, R. (2013). No Minneapolis cops have been disciplined after 439 complaints. Retrieved from https://www.startribune.com/no-minneapolis-cops-have-been-disciplined-after-439-complaints/221422101/


and controlling police abuse of force (pp. 23–51). New Haven, CT: Yale University Press


APPENDICES

Appendix 1. Definitions and examples of use of force according to the Attorney General's Use of Force Policy (Issued April 1985; Revised June 2000)

<table>
<thead>
<tr>
<th>A. Constructive Authority</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Constructive authority does not involve actual physical contact with the subject but involves the use of the law enforcement officer’s authority to exert control over a subject.</td>
</tr>
<tr>
<td>2. Examples include verbal commands, gestures, warnings, and unholstering a weapon.</td>
</tr>
<tr>
<td>3. Pointing a firearm at a subject is an element of constructive authority to be used only in appropriate situations.¹</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>B. Physical Contact</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Physical contact involves routine or procedural contact with a subject necessary to effectively accomplish a legitimate law enforcement objective.</td>
</tr>
<tr>
<td>2. Examples include guiding a subject into a police vehicle, holding the subject’s arm while transporting, handcuffing a subject and maneuvering or securing a subject for a frisk.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>C. Physical Force</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Physical force involves contact with a subject beyond that, which is generally utilized to effect an arrest or other law enforcement objective. Physical force is employed when necessary to overcome a subject’s physical resistance to the exertion of the law enforcement officer’s authority, or to protect persons or property.</td>
</tr>
<tr>
<td>2. Examples include wrestling a resisting subject to the ground, using wrist locks or arm locks, striking with the hands or feet, or other similar methods of hand-to-hand confrontation.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>D. Mechanical Force</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Mechanical force involves the use of some device or substance, other than a firearm, to overcome a subject’s resistance to the exertion of the law enforcement officer’s authority.</td>
</tr>
<tr>
<td>2. Examples include the use of a baton or other object, canine physical contact with a subject, or chemical or natural agent spraying.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>E. Deadly Force</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Deadly force is force which a law enforcement officer uses with the purpose of causing or which the officer knows to create a substantial risk of causing death or serious bodily harm.</td>
</tr>
<tr>
<td>2. Purposely firing a firearm in the direction of another person or at a vehicle, building or structure in which another person is believed to be constitutes deadly force.</td>
</tr>
<tr>
<td>3. A threat to cause death or serious bodily harm by the production of a weapon or otherwise, so long as the officer’s purpose is limited to creating an apprehension that deadly force will be used if necessary, does not constitute deadly force.</td>
</tr>
</tbody>
</table>

Notes.
¹ Pointing a firearm at a civilian is not required to be reported.
² Under the guidelines suggested by the Attorney General, Use of Force Reports are only required if physical force, mechanical force, or deadly force is used. However, departments may vary in how they elect to record these incidents.
Appendix 2. Definitions and examples of use of force according to the Jersey City Police Department

USE OF FORCE REPORT FORM REQUIRED FOR ALL ACTIONS TO THE RIGHT OF THIS LINE

Physical Contact
- Gripping suspect into patrol car
- Holding prisoner arm while transporting
- Handcuff suspect/prisoner
- Mating or securing suspect for flight

Mechanical Force
- Use of tasers or other object
- Other physical contact with suspect
- Chemical or natural agent spraying

Deadly Force
- Firearms
- Other means

INSTRUCTIONS FOR USE OF FORCE REPORT

A. INCIDENT INFORMATION

This section requests information on the incident that involved police use of force. Please provide the date and time of the force incident. For "Day of Week," use the standard three-letter abbreviation (Monday, Monday-Plus, etc.). For location, use the street address.

B. SUSPECT(S) INFORMATION

This section requests information on the suspect(s) involved in the use of force incident. Information should be filled out only for those suspects that were involved in police use of force. If the suspect escaped, include "escaped" for name. For weapons, please check "Y" if any weapon was found on the suspect. For "Wore and breathed," check "Y" only if suspect's inhalation caused physical use of force.

C. LEVEL OF SUSPECT RESISTANCE

This section requests information on the level of resistance used by the suspect. Check off every level of resistance that the suspect used. For example, if suspect threatened/assaulted with both inner weapons and firearm, both boxes would be checked. Use the flat columns marked "Suspect 1" if only one suspect is involved.

D. TYPE OF FORCE USED

This section requests information on the level of force you used in the incident. Check off all levels of force you used against the suspect. If you utilized a type of force not included on the form, please check "Other Force" and specify your action in the space provided.

E. OFFICER INFORMATION

This section requests information from you. For listing and dropping information, circle "Y" only for injuries you received during the force incident. For "Police Officer Assigned," indicate the type of unit you were assigned to on the day of the incident, and, if applicable, the sector or beat you were assigned to.
Appendix 3. Use of Force Report, New Jersey

**POLICE DEPARTMENT**

**USE OF FORCE REPORT**

<table>
<thead>
<tr>
<th>Date</th>
<th>Time</th>
<th>Day of Week</th>
<th>Location</th>
<th>INCIDENT NUMBER</th>
</tr>
</thead>
</table>

**Type of Incident**
- ☐ Crime in progress
- ☐ Domestic
- ☐ Other dispute
- ☐ Suspicious person
- ☐ Traffic stop
- ☐ Other (specify)

**B. Officer Information**

<table>
<thead>
<tr>
<th>Name (Last, First, Middle)</th>
<th>Badge #</th>
<th>Sex</th>
<th>Race</th>
<th>Age</th>
<th>Injured</th>
<th>Y / N</th>
<th>Killed</th>
<th>Y / N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rank</td>
<td>Duty assignment</td>
<td>Years of service</td>
<td>On-Duty</td>
<td>Uniform</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**C1. Subject 1** (List only the person who was the subject of the use of force by the officer listed in Section B.)

<table>
<thead>
<tr>
<th>Name (Last, First, Middle)</th>
<th>Sex</th>
<th>Race</th>
<th>Age</th>
<th>Weapon</th>
<th>Injured</th>
<th>Y / N</th>
<th>Killed</th>
<th>Y / N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Under the influence</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Other unusual condition (specify)</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Subject’s actions (check all that apply)</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
</tbody>
</table>
- ☐ Resisted police officer control
- ☐ Physical threat/attack on officer or another
- ☐ Threatened/attacked officer or another with blunt object
- ☐ Threatened/attacked officer or another with knife/cutting object
- ☐ Threatened/attacked officer or another with motor vehicle
- ☐ Threatened officer or another with firearm
- ☐ Fired at officer or another
- ☐ Other (specify)

| Officer’s use of force toward this subject (check all that apply) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
- ☐ Compliance hold
- ☐ Hands/feet
- ☐ Kicks/feet
- ☐ Chemical/natural agent
- ☐ Strike/use baton or other object
- ☐ Vehicle
- ☐ Other (specify)

**C2. Subject 2** (List only the person who was the subject of the use of force by the officer listed in Section B.)

<table>
<thead>
<tr>
<th>Name (Last, First, Middle)</th>
<th>Sex</th>
<th>Race</th>
<th>Age</th>
<th>Weapon</th>
<th>Injured</th>
<th>Y / N</th>
<th>Killed</th>
<th>Y / N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Under the influence</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Other unusual condition (specify)</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Subject’s actions (check all that apply)</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
</tbody>
</table>
- ☐ Resisted police officer control
- ☐ Physical threat/attack on officer or another
- ☐ Threatened/attacked officer or another with blunt object
- ☐ Threatened/attacked officer or another with knife/cutting object
- ☐ Threatened/attacked officer or another with motor vehicle
- ☐ Threatened officer or another with firearm
- ☐ Fired at officer or another
- ☐ Other (specify)

| Officer’s use of force toward this subject (check all that apply) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
- ☐ Compliance hold
- ☐ Hands/feet
- ☐ Kicks/feet
- ☐ Chemical/natural agent
- ☐ Strike/use baton or other object
- ☐ Vehicle
- ☐ Other (specify)

If this officer used force against more than two subjects in this incident, attach additional USE OF FORCE REPORTS.

<table>
<thead>
<tr>
<th>Signature:</th>
<th>Date:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Print Supervisor Name:</td>
<td>Supervisor Signature:</td>
</tr>
</tbody>
</table>

7/2001
# Appendix 4. Use of Force Report, Jersey City Police Department

## J. CITY POLICE DEPARTMENT

### USE OF FORCE REPORT

#### A. INCIDENT INFORMATION

<table>
<thead>
<tr>
<th>Type of Incident</th>
<th>Date</th>
<th>Time</th>
<th>Day of Week</th>
<th>Location</th>
<th>File Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crime In progress</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Domestic</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other Dispute</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Suspicious Person</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Traffic Stop</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### B. OFFICER INFORMATION

<table>
<thead>
<tr>
<th>Name (Last, First, Middle)</th>
<th>Badge #</th>
<th>Sex</th>
<th>Race</th>
<th>Age</th>
<th>Injured</th>
<th>Killed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Y/N</td>
<td>Y/N</td>
<td>Y/N</td>
<td>Y/N</td>
<td>Y/N</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Rank</th>
<th>Duty Assignment</th>
<th>Years of Service</th>
<th>On Duty</th>
<th>Uniform</th>
<th>Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Y/N</td>
</tr>
</tbody>
</table>

#### C1. SUBJECT 1

(List only the person who was the subject of the use of force by the officer listed in Sec.B.)

<table>
<thead>
<tr>
<th>Name (Last, First, Middle)</th>
<th>Under the Influence</th>
<th>Other unusual condition (specify)</th>
<th>Arrested</th>
<th>Charges</th>
<th>Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Y/N</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Subject's actions (check all that apply)</th>
<th>Officer's use of force toward this subject (check all that apply)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resisted police officer control</td>
<td>Compliance hold</td>
</tr>
<tr>
<td>Physical threat/attack on officer or another</td>
<td>Firearms Discharge</td>
</tr>
<tr>
<td>Threatened/attacked officer or another with blunt object</td>
<td>Intentional</td>
</tr>
<tr>
<td>Threatened/attacked officer or another with kicks/punching object</td>
<td>Accidental</td>
</tr>
<tr>
<td>Threatened/attacked officer or another with chemical/chemical agent</td>
<td>Number of shots fired</td>
</tr>
<tr>
<td>Threatened/attacked officer or another with motor vehicle</td>
<td></td>
</tr>
<tr>
<td>Threatened officer or another with firearm</td>
<td></td>
</tr>
<tr>
<td>Fired at officer or another</td>
<td></td>
</tr>
<tr>
<td>Other (specify)</td>
<td></td>
</tr>
</tbody>
</table>

#### C2. SUBJECT 2

(List only the person who was the subject of the use of force by the officer listed in Sec.B.)

<table>
<thead>
<tr>
<th>Name (Last, First, Middle)</th>
<th>Under the Influence</th>
<th>Other unusual condition (specify)</th>
<th>Arrested</th>
<th>Charges</th>
<th>Y/N</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Y/N</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Subject's actions (check all that apply)</th>
<th>Officer's use of force toward this subject (check all that apply)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resisted police officer control</td>
<td>Compliance hold</td>
</tr>
<tr>
<td>Physical threat/attack on officer or another</td>
<td>Firearms Discharge</td>
</tr>
<tr>
<td>Threatened/attacked officer or another with blunt object</td>
<td>Intentional</td>
</tr>
<tr>
<td>Threatened/attacked officer or another with kicks/punching object</td>
<td>Accidental</td>
</tr>
<tr>
<td>Threatened/attacked officer or another with chemical/chemical agent</td>
<td>Number of shots fired</td>
</tr>
<tr>
<td>Threatened officer or another with firearm</td>
<td></td>
</tr>
<tr>
<td>Fired at officer or another</td>
<td></td>
</tr>
<tr>
<td>Other (specify)</td>
<td></td>
</tr>
</tbody>
</table>

---

If this officer used force against more than two subjects in this incident, attach additional Use of Force Reports.

Signature:  

Print Supervisor Name:  

Supervisor Signature:  

"Attachment B"
### Appendix 5. Description of variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Incident Level</strong></td>
<td></td>
</tr>
<tr>
<td>Incident ID</td>
<td>Unique ID number identifying the case [derived from the case report number, date of the incident]</td>
</tr>
<tr>
<td>County</td>
<td>County where the event occurred</td>
</tr>
<tr>
<td>Town</td>
<td>Responding police department</td>
</tr>
<tr>
<td>Incident date</td>
<td>Reported date</td>
</tr>
<tr>
<td>Incident time</td>
<td>Time when the event happened</td>
</tr>
<tr>
<td>Location city</td>
<td>City where the event happened</td>
</tr>
<tr>
<td>Location detail</td>
<td>Address (or other location detail, like a school, hospital, or casino) where the event happened</td>
</tr>
<tr>
<td>Incident type</td>
<td>Type of incident, e.g., traffic stops, domestic, etc.</td>
</tr>
<tr>
<td>Incident EDP¹</td>
<td>Indicates whether the incident involved an &quot;emotionally disturbed person&quot;</td>
</tr>
<tr>
<td>Firearms used</td>
<td>Indicates if a firearm was discharged or pointed at the subject(s). [derived from firearms discharged or firearms pointed]</td>
</tr>
<tr>
<td>Firearms discharged</td>
<td>Indicates if the firearm was discharged accidentally or intentionally</td>
</tr>
<tr>
<td>Firearms pointed</td>
<td>Indicates if the firearm was pointed</td>
</tr>
<tr>
<td>Firearms shots no</td>
<td>Indicates the number of shots fired</td>
</tr>
<tr>
<td><strong>Officer Level</strong></td>
<td></td>
</tr>
<tr>
<td>Officer unique ID</td>
<td>Unique ID number identifying the officer [derived from the first name, middle name, last name, sex, race, badge no., town]</td>
</tr>
<tr>
<td>Officer first</td>
<td>First name of the officer involved in the incident</td>
</tr>
<tr>
<td>Officer middle</td>
<td>Middle name of the officer involved in the incident</td>
</tr>
<tr>
<td>Officer last</td>
<td>Last name of the officer involved in the incident</td>
</tr>
<tr>
<td>Officer rank</td>
<td>Rank, e.g., patrolman, detective, etc.</td>
</tr>
<tr>
<td>Officer exp</td>
<td>Years of experience of an officer (all fields in years)</td>
</tr>
<tr>
<td>Officer sex</td>
<td>Sex</td>
</tr>
<tr>
<td>Officer race</td>
<td>Race</td>
</tr>
<tr>
<td>Officer badge no</td>
<td>Badge number</td>
</tr>
<tr>
<td>Officer injured</td>
<td>Indicates whether the officer was injured</td>
</tr>
<tr>
<td>Officer hospitalized</td>
<td>Indicates whether the officer was hospitalized</td>
</tr>
<tr>
<td>Officer killed</td>
<td>Indicates whether the officer was killed</td>
</tr>
<tr>
<td><strong>Supervisor Level</strong></td>
<td></td>
</tr>
<tr>
<td>Supervisor Unique ID</td>
<td>Unique ID number identifying the supervisor [derived from the first name, middle name, last name, badge no., town]</td>
</tr>
<tr>
<td>Supervisor first</td>
<td>First name of the supervisor who signed the report</td>
</tr>
<tr>
<td>Supervisor last</td>
<td>Last name of the supervisor who signed the report</td>
</tr>
<tr>
<td>Supervisor badge no</td>
<td>Badge number of the supervisor who signed the report</td>
</tr>
<tr>
<td>Supervisor signed</td>
<td>Indicates whether a supervisor signed the report</td>
</tr>
<tr>
<td>------------------</td>
<td>--------------------------------------------------</td>
</tr>
<tr>
<td><strong>Subject Level</strong>²</td>
<td></td>
</tr>
<tr>
<td>Subject ID</td>
<td>First and last name of the subject</td>
</tr>
<tr>
<td>Subject age</td>
<td>Age</td>
</tr>
<tr>
<td>Subject race</td>
<td>Race</td>
</tr>
<tr>
<td>Subject sex</td>
<td>Sex</td>
</tr>
<tr>
<td>Subject actions</td>
<td>Actions that led to force being used on them</td>
</tr>
<tr>
<td>Subject charges</td>
<td>Charges against subject</td>
</tr>
<tr>
<td>Subject force nature</td>
<td>Nature of force used on the subject</td>
</tr>
<tr>
<td>Subject injured</td>
<td>Indicates if the subject was injured during the incident</td>
</tr>
<tr>
<td>Subject hospital</td>
<td>Indicates whether the subject was hospitalized during the incident</td>
</tr>
<tr>
<td>Subject killed</td>
<td>Indicates whether the subject was killed during the incident</td>
</tr>
<tr>
<td>Subject photo</td>
<td>Indicates if there are photos attached to the report</td>
</tr>
<tr>
<td>Narrative</td>
<td>Contains narrative of the incident if any</td>
</tr>
</tbody>
</table>

Note.

¹ The “Incident EDP” column was created based on whether the incident type appeared to record the incident as an emotionally distressed person. It is not a comprehensive column.

² No subject level variables are used in the analysis.
### Appendix 6. Distribution of data nested into counties (the number of departments, unique supervisors, unique officers, use of force incidents, and use of force reports)

<table>
<thead>
<tr>
<th>County</th>
<th>Departments</th>
<th>Supervisors</th>
<th>Officers</th>
<th>Use of Force Incidents</th>
<th>Use of Force Reports</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlantic County</td>
<td>16</td>
<td>321</td>
<td>862</td>
<td>2,748</td>
<td>4,618</td>
</tr>
<tr>
<td>Bergen County</td>
<td>68</td>
<td>585</td>
<td>1,354</td>
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<td>843</td>
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<td>1,425</td>
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</table>

**Total N**: 461, 6,490, 17,845, 43,389, 69,194

**Note.**

\(^1\) In addition to acting as the official state police force of New Jersey, the New Jersey State Police has served Manchester - Ocean County, Berkeley - Ocean County, and Ventnor City - Atlantic County.
### Appendix 7. Profile of department

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Definition</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size of the department</td>
<td>Number of sworn full-time officers employed, per department</td>
<td>New Jersey Crime Reports</td>
</tr>
<tr>
<td>Volume of force</td>
<td>Number of Force Reports filed, per department</td>
<td>Force Report</td>
</tr>
<tr>
<td>Sex</td>
<td></td>
<td>New Jersey Crime Reports</td>
</tr>
<tr>
<td>Proportion Male</td>
<td>Number of unique male officers, relative to the size of the department</td>
<td>LEMAS</td>
</tr>
<tr>
<td>Proportion Female</td>
<td>Number of unique female officers, relative to the size of the department</td>
<td></td>
</tr>
<tr>
<td>Race/ Ethnicity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion White</td>
<td>Number of White officers, relative to the size of the department</td>
<td></td>
</tr>
<tr>
<td>Proportion Black</td>
<td>Number of Black officers, relative to the size of the department</td>
<td></td>
</tr>
<tr>
<td>Proportion Hispanic</td>
<td>Number of Hispanic officers, relative to the size of the department</td>
<td></td>
</tr>
<tr>
<td>Proportion Other</td>
<td>Number of unique “other” officers, per department (comprised of officers who identified as American Indian or Alaskan Native, Asian, Hawaiian, two or more races, other, and unknown), relative to the size of the department</td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>No minimum education requirement or at least a high school diploma or equivalent required for new sworn hires</td>
<td>LEMAS</td>
</tr>
<tr>
<td>High school</td>
<td>No minimum education requirement or at least a high school diploma or equivalent required for new sworn hires</td>
<td></td>
</tr>
<tr>
<td>Associate degree</td>
<td>Associate degree or equivalent required for new sworn hires</td>
<td></td>
</tr>
<tr>
<td>College/Bachelor’s Degree</td>
<td>Some college or a bachelor’s degree or equivalent required for new sworn hires</td>
<td></td>
</tr>
<tr>
<td>Type of force used¹</td>
<td>Type of force, relative to the volume of force per department</td>
<td>Force Report</td>
</tr>
<tr>
<td>Proportion Constructive Force</td>
<td>Pointing or drawing a firearm,</td>
<td></td>
</tr>
<tr>
<td>Proportion Physical Contact/ Physical Force</td>
<td>Guiding a subject into a police vehicle, holding the subject’s arm while transporting, handcuffing a subject and maneuvering or securing a subject for a frisk; wrestling a resisting subject to the ground, using wrist locks or arm locks, striking with the hands or feet, or other</td>
<td></td>
</tr>
</tbody>
</table>
similar methods of hand-to-hand confrontation.

**Proportion Mechanical Force**
The use of a baton or other object, canine physical contact with a subject, or chemical or natural agent spraying.

**Proportion Deadly Force**
Purposefully firing a firearm in the direction of another person, vehicle, building, or structure; force which a law enforcement officer uses with the purpose of causing, or which the officer knows to create a substantial risk of causing death or serious bodily harm.

**Diversity Index**
A measure of specialization and versatility in use of force behaviors, per department.

**Municipal offense and demographic data**
Each law enforcement department in the study was matched with the municipality that they police.

**Estimated population**
Mean estimated population for the municipality averaged across years 2012-2016.

**Crime rate, per 1000**
Mean crime rate, per 1000, for the municipality averaged across 2012-2016.

**Rural**
Is the municipality considered a Rural area.

**Suburban**
Is the municipality considered a Suburban area.

**Urban**
Is the municipality considered an Urban area.

**New Jersey Crime Reports**

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**Note.**

1 In incidents where officers resort to using more than one type of force, in a single use of force incident, the most lethal type of force is measured.

2 Data on the population, crime rate, and whether the municipality is considered Rural, Suburban, or Urban from 2012 to 2016 were retrieved from [https://www.njsp.org/ucr/uniform-crime-reports.shtml](https://www.njsp.org/ucr/uniform-crime-reports.shtml). These reports are based on crime statistics submitted to the New Jersey Uniform Crime Reporting System by every New Jersey law enforcement agency for the year 2012 to 2016.

3 Crime rates are based on year-round populations. Crimes were based on the municipality of occurrence and were not computed for municipalities with a population of less than 100. 3

4 Only 122 departments in New Jersey were included in the survey. Of the 122 departments, 114 were matched with the Force Report. These data can be obtained from [https://www.icpsr.umich.edu/web/NACJD/studies/36164/versions/V2](https://www.icpsr.umich.edu/web/NACJD/studies/36164/versions/V2)
### Appendix 8. Profile of groups delineated by the Leiden algorithm

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Size</strong></td>
<td>Number of officers, per community</td>
</tr>
<tr>
<td><strong>Density</strong>&lt;sup&gt;1&lt;/sup&gt;</td>
<td>The degree to which a community is connected (i.e., a measure of the proportion of possible ties that are actualized among the officers of a community)</td>
</tr>
<tr>
<td><strong>Departments</strong></td>
<td>Number of departments represented, per community</td>
</tr>
<tr>
<td><strong>Sex</strong></td>
<td></td>
</tr>
<tr>
<td>Proportion male</td>
<td>Number of male officers, relative to the size of the community</td>
</tr>
<tr>
<td>Proportion female</td>
<td>Number of female officers, relative to the size of the community</td>
</tr>
<tr>
<td><strong>Race/ Ethnicity</strong></td>
<td></td>
</tr>
<tr>
<td>Proportion White</td>
<td>Number of White officers, relative to the size of the community</td>
</tr>
<tr>
<td>Proportion Black</td>
<td>Number of Black officers, relative to the size of the community</td>
</tr>
<tr>
<td>Proportion Hispanic</td>
<td>Number of Hispanic officers, relative to the size of the community</td>
</tr>
<tr>
<td><strong>Experience/ tenure (years)</strong></td>
<td>Experience/ tenure of officers, per community</td>
</tr>
<tr>
<td><strong>Officer Movement</strong></td>
<td>Number of Force Reports filed in <em>multiple departments</em>, per community</td>
</tr>
<tr>
<td><strong>Force Reports</strong></td>
<td>Number of Force Reports, per community</td>
</tr>
<tr>
<td><strong>Force Strength</strong></td>
<td>Number of force reports, relative to the size of the community</td>
</tr>
<tr>
<td><strong>Network Capital</strong></td>
<td>Network capital score, per community</td>
</tr>
</tbody>
</table>

**Note.**

<sup>1</sup>Density and number of actualized ties were calculated only for communities with four or more unique officers, excluding 25 communities where three or fewer officers reported using force.
Note. The map shows correlation coefficients for all pairs of variables (with deeper colors representing stronger correlations). Correlations not significantly different from 0 are in white. [p<0.05]

Appendix 9. Pearson’s r correlation matrix at the group-level (n=31)
## Appendix 10. Profile of groups by network capital

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<th>Female</th>
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### Appendix 11. Summary of network capital measure, officer level (n=2,760)

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Note.  
1 The degree, betweenness, and closeness centrality are standardized and range from a value of 0 to 1.  
ABBREVIATIONS. Stdz = Standardized. SD = Standard Deviation.