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Author
Gravel, Jason

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On the use of police records for social network analysis

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Criminology, Law, and Society

by

Jason Gravel

Dissertation Committee:
Professor George E. Tita, Chair
Professor Katherine Faust
Professor Michael R. Gottfredson
Professor John R. Hipp
Professor Cheryl L. Maxson

2018

DEDICATION

À ma mère Sylvie.
Tout ça a commencé quand tu m'asseyais dans le salon pour m'apprendre à lire. Tu m'as donné une longueur d'avance sur les autres mais tu m'as surtout appris à ne jamais "niveler par le bas".

À mon père Luc.
Tu m'as montré que tu n'as pas besoin d'aller à l'école longtemps pour être brillant et faire ta part pour rendre le monde meilleur. Mais tu m'as toujours poussé à y aller quand même, juste au cas…

À mes soeurs Émilie et Ariane.
Mes meilleures et premières vraies amies. Chaque fois que je reviens à la maison, vous me faites sentir comme si je n'étais jamais partis avec vos niaiseries. J'espère que vos enfants vont jouer aux "personnages" aussi!
"Longue vie au roi! "-Scar

À Logan, Olivier, et Maxyme
(histoires à venir)

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ACKNOWLEDGMENTS

CURRICULUM VITAE

Jason Gravel

2009   B.A. in Psychology, Université Laval

2013   M.A. in Criminology, Simon Fraser University

2018   Ph.D. in Criminology, Law, & Society, University of California, Irvine

FIELD OF STUDY

Criminology, social network analysis, street gangs, crime prevention and intervention

PUBLICATIONS

Barragan, M., Chesnut, K., **Gravel, J.,** Pifer, N., Reiter, K., Sherman, N., & Tita, G. E. (2017) Prohibited possessors and the law: How inmates in Los Angeles jails understand firearm regulations. *RSF: The Russell Sage Foundation Journal of the Social Sciences, 3*(5), 141–163.
□
Gallupe, O., & **Gravel, J.** (2017). Social network position of gang members in schools: Implications for recruitment and gang prevention. *Justice Quarterly*. doi: 10.1080/07418825.2017.1323114.

Gravel, J., Wong, J. S., & Simpson, R. (2017). Getting in People's Faces: On the symbiotic relationship between the media and police gang units. *Deviant Behavior*. doi: 10.1080/01639625.2016.1269547.

Gushue, K., Lee, C., **Gravel, J.**, & Wong, J. S. (2017). Familiar gangsters: Gang violence, brotherhood, and the media's fascination with a crime family. *Crime & Delinquency*. doi: 10.1177/0011128716686340.

Gravel, J., Allison, B., West-Fagan, J., McBride, M., & Tita, G. E. (2016). Birds of a feather fight together: Status-enhancing violence, social distance and the emergence of racially and ethnically homogenous gangs. *Journal of Quantitative Criminology,* doi:10.1007/s10940-016-9331-8.

Chesnut, K., Barragan, M., **Gravel, J.**, Pifer, N., Reiter, K., Sherman, N., & Tita, G. E. (2016). Not an "iron pipeline", but many capillaries: Regulating passive transactions in Los Angeles' secondary illegal gun market. *Injury Prevention,* Online First, doi: 10.1136/injuryprev-2016-042088.

Wong, J. S., Bouchard, J., **Gravel, J.**, Bouchard, M., & Morselli, C. (2016). Can at-risk youth be diverted from crime? A meta-analysis of restorative justice diversion programs. *Criminal Justice and Behavior.* 43(10), 1310-1329.

Wong, J. S. & **Gravel, J.** (2016). Do sex offenders have higher levels of testosterone? Results from a meta- analysis. *Sexual Abuse: A Journal of Research and Treatment.* Online First, doi: 10.1177/1079063216637857.

Wong, J. S., **Gravel, J.,** Bouchard, M., Descormiers, K., & Morselli, C. (2016). Promises kept? A meta-analysis of gang membership prevention programs. *Journal of Criminological Research Policy and Practice, 2*(2), 134- 147. □

Gravel, J. & Tita, G. E. (2015). With great methods come great responsibilities: Social network analysis in the implementation and evaluation of gang programs. *Criminology and Public Policy, 14*(3), 559-572.

Gravel, J., Bouchard, M., Descormiers, K., Wong, J. S., & Morselli, C. (2013). Keeping Promises: A systematic review and a new classification of gang control strategies. *Journal of Criminal Justice, 41*(4), 228-242.

ABSTRACT OF THE DISSERTATION

On the use of police records for social network analysis

By

Jason Gravel

Doctor of Philosophy in Criminology, Law, & Society

University of California, Irvine, 2018

Professor George E. Tita, Chair

Social networks have always an important place in criminological theories. Despite their clear theoretical importance in explanations of crime and criminal behavior, social networks are all too often measured indirectly or not at all. Social network analysis (SNA) provides scholars with a set of measures, techniques, and models to directly investigate the impact of networks on behaviors but criminologists have taken longer than scholars in other fields to adopt SNA. Recently, scholars have begun using arrest and Field interview (FI) records to extract relationships between individuals encountered by the police. This dissertation provides a first critical analysis of the implications of using police records to study criminal social networks. I examine to what extent these networks reflect the behaviors of actors involved in them or the behaviors of organizations that observe them. I provide an in-depth description of the nature and content of arrest and FI records that are critical to the construction of social networks. I explore sources of variations in police records based on police organizational changes such as changes in leadership, and reduction in the size of the police force, and police adaptations to important legal changes that occurred in recent years in California. I also test the influence of civil gang injunctions on both the patterns of associations of gang members targeted by them and the

behavior of officers enforcing the injunctions. I discuss the implications of using these records to measure criminal social networks.

PREFACE

In 2011, Papachristos (2011, p.101) argued that criminologists had "missed the boat on [the] diffusion of social network analysis" that was happening in many fields of social sciences. Seven years later, criminologists have not yet caught up with the boat, but are swimming and getting very close to it. It is increasingly common to see papers using social network analysis being published in criminology journals, thanks in large part to the work of Andrew Papachristos in the United States, and Carlo Morselli and Pierre Tremblay in Canada. The recent growth of network studies of crime is to a considerable extent due to the increasing use of police records to construct social networks to study the dynamics of co-offending relationships, the stability of criminal groups, the structure of gang networks, the influence of gangs in the diffusion of firearms and violent victimization. Based on the research that was being conducted when I began working on my dissertation in 2014, the prospect of using police data to answer questions related to social structure of street gangs and co-offending seemed like an innovative avenue.

I originally proposed to use networks constructed from police records to study the structure of street gangs and examine whether the co-offending networks of gang members differed in some respects from those of non-gang members, among other things. Another part of the proposal I presented to my dissertation committee was to explore the data generating process behind the types of records typically used for the construction of social networks. I envisioned this part of my dissertation as more or less the typical "data" chapter of a research project, where researchers outline the steps undertaken to clean, prepare the data for the analysis, and outline the several limitations associated with the use of the data. It would be an understatement to say that I did not foresee this process being as tedious as it turned out to be. The "data chapter" I began working on nearly four years ago never really ended.

When I constructed networks from the police data I obtained from the Long Beach Police Department, I realized that networks from the first few years of data looked very different from those from the last few years of data. The number of relationships extracted from the police records plummeted after the first three years of data, decreasing almost by half. I first thought that something went wrong during the cleaning of the data and construction of the networks, but after meticulously retracing my steps several times, I had to conclude that something else was going on. When I began investigating what could have caused this sudden and drastic decrease in the number of relationships recorded by police officers, I realized just how many important changes occurred during the period I was studying that could have influenced police work and by extension, the data generating process behind the data I was analyzing. I decided to refocus my efforts towards exploring how the structure of networks extracted from police data can be impacted by changes in policy and police organizations.

This dissertation became the first critical analysis of the use of police records for social network analysis. To date, research employing similar data has been largely uncritical of the implications of using police data to construct social networks. To be fair, scholars often point out that when using such data we have to be conscious of the typical well-known biases associated with police data such as the tendency of the police to disproportionately encounter certain populations and target certain communities. Moreover, researchers typically note that police data is unlikely to contain information about all crimes committed and all criminals involved in crimes. After all, many crimes (if not the majority) never come to the attention of the police. Unfortunately, these observations are often limited to a few lines in a limitation section of a paper. My analyses revealed that the limitations of using police data are likely to be more important than what has previously been reported in prior studies.

What started as a study of gangs, co-offending and social networks quickly became a study of policing. Police organizations constantly have to adapt to various external pressures related to changes in policy, legal changes, and budgetary constraints. The contribution of this dissertation is to consider how these changes and adaptation may influence the data generating process behind the records used for social network analysis.

CHAPTER 1. SOCIAL NETWORK ANALYSIS OF POLICE DATA

Introduction

Social networks have always held an important place in criminological theories. Crime is often committed in the company of peers (e.g. Reiss & Farrington, 1991; Warr, 2002). The techniques and attitudes that facilitate the commission of crimes can be learned through associations with others (e.g. Burgess, & Akers, 1966; Sutherland, 1939) and access to some criminal opportunities depends on associations with more experienced offenders (Cloward & Ohlin, 1960). In communities where crime is most prevalent, it has been argued that criminal values are diffused through subcultures (e.g. Cohen, 1955; Miller, 1958) and playgroups morph into the more criminogenic youth gangs that vary in their group structures (e.g. Klein, 1971; Short & Strodtbeck, 1965; Thrasher, 1927). Social networks are also crucial to the prevention of crime by enabling trust, solidarity and cooperation between residents of a community to serve as informal sources of social control (e.g. Bursik & Grasmick, 1993; Sampson & Groves, 1989).

Despite their clear theoretical importance in explanations of crime and criminal behavior (e.g. Krohn, 1986; Weerman, 2003), social networks are all too often measured indirectly or not at all (Morselli, 2009). Not so long ago, Mitchell (1969, p.2) had a similar critique about the use of social networks in sociology and anthropology:

"The image of 'network of social relations' to represent a complex set of inter-relationships in a social system has had a long history. This use of 'network', however is purely metaphorical and is different from the notion of a social network as a specific set of linkages among a defined set of persons with the additional property that the characteristics of these linkages as a whole may be used to interpret social behavior of the persons involved."

Social network analysis (SNA) can be described as both a theoretical perspective and a methodology. It can be thought of as a theoretical perspective because when using SNA, scholars are making an "assumption about the importance of relationships among interacting units"

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(Wasserman & Faust, 1994; p.4). These units can be individuals, groups, events, or communities; the interactions can be friendships, bonds of trust, rivalries, alliances, etc. SNA, as a methodology, provides measures to describe and techniques to model the patterns and structures that emerge from these interactions.

While SNA has become a staple in many social sciences (Borgatti, Mehra, Brass & Labianca, 2009; Freeman, 2004), criminology seemed to have, as Papachristos (2011, p.101) put it, "missed the boat" on the spread of SNA, with only a handful of papers by a small group of researchers being published in the top criminology journals as of 2010. Although criminologists are increasingly taking advantage of SNA (Morselli, 2014), many have recently lamented its neglect, especially given the importance given to different dimensions of social networks in criminological theories (Bouchard & Malm, 2016; Carrington, 2011; Gravel & Tita, 2017; McGloin & Kirk, 2011;McGloin & Nguyen, 2014; Morselli, 2009; Papachristos, 2011; Sarnecki, 2001; Tita & Boessen, 2011).

Notwithstanding the work of a few pioneers (e.g. Klein & Crawford, 1967; Sarnecki, 1986), criminologists have only recently begun to move away from invoking "metaphorical" networks, to use Mitchell's words, and explicitly measure networks and using the tools of SNA. Despite a slow start in adopting SNA (Papachristos, 2011), it is quickly becoming an important tool in criminological research (e.g. Bouchard & Malm, 2016; Gravel & Tita, 2017; Sierra-Arevalo & Papachristos, 2017; Morselli, 2014). A primary reason why SNA has taken longer to take hold in criminology compared to other fields of social and behavioral sciences (e.g. Borgatti, Mehra, Brass, & Labianca, 2009; Freeman, 2004) likely has to do with the added difficulties associated with measuring networks of actors who would rather stay in the shadows. Criminologists interested in social networks have had to think of clever ways to indirectly

measure what some have called "dark networks"—networks of actors who actively seek to conceal their activities, typically from authorities (Raad & Milward, 2003; Everton, 2012).

In some cases, scholars have used biographies (e.g. Morselli, 2003), newspaper articles (Krebs, 2002), court documents and government inquiries (Baker & Faulkner, 1993; Nash, Bouchard, & Malm, 2013; Ouellet, Bouchard, & Hart, 2017), wiretap investigations (Morselli, 2009) and tax investigations (Smith & Papachristos, 2016) to name but a few. In rare occasions, criminologists have mapped patterns of relationships from observations (Fleisher, 2005; Hughes & Short, 2005; Klein & Crawford, 1967; Klein, 1971; Suttles, 1968), and have used informants and police intelligence to map relationships between criminal groups (Descormiers & Morselli, 2011; McGloin, 2005; Papachristos, 2009; Tita & Radill, 2011; Valasik, 2014).

Surveys and interviews have also been an important source of network data in recent years, primarily thanks to the availability of network data in school settings and indicators of delinquent behavior from the National Longitudinal Study of Adolescent to Adult Health (Harris, Halpern, Whitsel, Hussey, Tabor, Entzel & Udry, 2009; commonly referred to as Add Health). In fact, Haynie's (2001) use of Add Health to demonstrate the importance of considering the structure of peer networks when studying peer influences on delinquency as been noted by many scholars as a turning point in the use of SNA in criminology (e.g. Bouchard & Malm, 2016; Papachristos, 2011). Several other school surveys similar to Add Health have emerged in the last few years, many of which were designed specifically to study delinquency (Knecht, Snijders, Baerveldt, Steglich, & Raub, 2010; Weerman, 2011; Weerman, Wilcox, & Sullivan, 2018). Scholars have also taken advantage of other closed settings such as prisons to study prison culture (Kreager, Schaefer, Bouchard, Haynie, Wakefield, Young, & Zajac, 2016; Kreager, Young, Haynie, Bouchard, Schaefer, & Zajac, 2017; Schaefer, Bouchard, Young, & Kreager,

2017). While schools offer an interesting setting to study where delinquency begins, and prisons, a setting to investigate those who persisted and were caught, much of what is of interest to criminologists happens in between.

In the hope of gaining a better understanding of how the structure of interactions between criminally active individuals in the community can inform criminological theories and criminal justice policies, criminologists have turned to police records. Police records of arrests and other types of encounters between police officers and members of the communities they serve are collected and maintained in databases in pretty much in all modern cities around the world. The coordination between law enforcement and other branches of the criminal justice apparatus require that such records are collected and stored similarly across jurisdictions. Invariably, these records include information about the individuals encountered by the police and the events that led to these encounters. From this information, it is possible to link individuals to one another through their participation in the same events. The widespread realization that network data has been lying under criminologists' noses this whole time is relatively recent, though some had begun exploring these networks earlier (e.g. Sarnecki, 1986; 1990; Sparrow, 1991).

In a relatively short time, network data extracted from arrest and other types of police records has contributed some interesting findings particularly regarding the contagion of gun violence and victimization (Green, Horel, & Papachristos, 2017; Papachristos, Braga, & Hureau, 2012; Papachristos & Wildeman, 2014; Papachristos, Wildeman, & Roberto, 2015; Tracy, Braga, & Papachristos, 2016), and the influence of street gangs in the transmission of violence (Papachristos, Braga, Piza, & Grossman, 2015) and in the diffusion of firearms (Roberto, Braga, & Papachristos, 2018). It has also played an important role in the design and evaluation of interventions designed to reduce violence, particularly gang violence (Gravel & Tita, 2015;

Kennedy, Piehl, & Braga, 1997; Papachristos & Kirk, 2015; Sierra-Arevalo, Charette, & Papachristos, 2017; Sierra-Arevalo & Papachristos, 2017; Tita, Riley, Ridgeway, Grammich, Abrahamse, & Greenwood, 2003). For all the potential SNA of police data holds, researchers have been rather silent regarding the limitations of their data, an omission rather uncharacteristic of a field with a long history of skepticism regarding police data and other official sources of crime data (Black, 1970; Blumstein, Cohen, & Rosenfeld, 1991; Sellin, 1931; Skolnick, 1966). The goal of this dissertation is to begin filling this gap by conducting a critical analysis of police records used to generate social network data.

Social network analysis of police records

One of the earliest studies to use arrest records to construct networks was conducted by Sarnecki (1986; 1990). The author used police data to create networks of young offenders in Stockholm by linking together youths that had been arrested for or suspected of committing the same crime. Sarnecki (1990) created the networks of 1403 juveniles who were suspected of having committed at least one crime between 1975 and 1984 and found that 45% of these juveniles could be linked to each other. He also found that individuals who were deemed to be the most delinquent were all connected to each other. Furthermore, the author argued that the most connected individuals in the networks remained present in the network for a longer period of time and were important sources of co-offending for younger individuals joining the networks in later years.

In his 1990 study, Sarnecki was critical of his own methodology and sought to test whether police data could in fact approximate juveniles' co-offending networks. The author states:

"The research methodology used here suffers from the same serious problems as those which affect all other criminological research methods that are based on information from the police

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regarding registered and cleared-up offenses. [...] It is, of course, extremely risky to draw conclusions about the actual delinquency in an area on the basis of this small fraction of all offenses committed" (Sarnecki, 1990, p. 34).

Few of the studies that have followed Sarnecki (1990), however, have conducted similar sensitivity analyses to assess the validity of co-offending network data. Sarnecki (1990) conducted interviews with a subset of delinquents in his sample to establish whether the ties created using co-arrest data reflected a relevant sample of meaningful relationships between juveniles. His analysis revealed significant overlap between the police network and friendship relationships between juveniles. Furthermore, the vast majority of the individuals his respondents nominated as "best friends" were found in the police data. Often they were connected to those who had nominated them, and almost all of them could at least be found somewhere in the network. Finally, Sarnecki (1990) found that the better-connected individuals in the networks were also those who received the most friendship nominations.

Sarnecki's study provided some evidence that co-arrest networks were at least representative of a sample of ties between juvenile offenders. However, his study was conducted in a small town in Sweden and focused on a small subset of offenders. More recent studies using co-arrest networks map these relationships over an entire country (e.g. Carrington, 2009), province (e.g. Ouellet, Boivin, Leclerc, & Morselli, 2013) or city (e.g. Gravel, 2013; Tremblay, Charest, Charette, & Tremblay-Faulkner, 2016). In these conditions, it is difficult to assess the validity of the data using the techniques Sarnecki used. Still, recent research on co-arrest networks while cautioning readers about the inherent limitations of police based data, have largely failed to examine these limitations in depth. A detailed and critical assessment of the data used to construct these types of networks is an important gap to fill in order for such data to be taken seriously.

The construction of social networks from police data

The construction of any network involves a set of actors (or nodes) and a set of relationships (or edges). The construction of social networks from police data often relies on two types of police records, or a combination of both: arrest records, and Field interview (FI) cards. Although the use and purpose of FI cards varies between police departments, they are typically records of police-citizen encounters that did not lead to a formal arrest (e.g. Papachristos, et al., 2015; Valasik, 2014). Technically, networks using arrest and FI records are two-mode networks. Modes of a network refer to the different sets of nodes that are included in the network, such as events and individuals in the present case. More precisely, because they only involve one set of actors and the second mode of the network are events, these networks are a special type of two-mode networks called affiliation networks (Wasserman & Faust, 1994). Although one could analyze the two-mode network itself, the majority of research using these data has examined the one-mode representation of this network where individuals have ties to others if they were involved in the same events.

Defining ties: Co-offending, co-arrest, and co-FI networks

While many of the recent studies employing police data to create social networks refer to them as co-offending networks, it is important to make a distinction between ties that arise from arrests or FI records and co-offending. Co-offending is not always treated as a clearly defined concept in the literature as it is often confounded with concepts of delinquent peers and group offending (Reiss, 1988; Reiss & Farrington, 1991; Warr, 2002; Weerman, 2003). In its most general form, co-offending refers to the commission of a crime in the company of others; Weerman (2003, p.398) argued that "co-offending embraces the actual collective execution of an offence" and Reiss and Farrington (1991, p.360) "refer to persons who act together in a crime as co-offenders and to their committing that crime as co-offending". For Tremblay (1993, p.20), co-

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offending refers "not only to the subset of an offender's pool of accomplices but rather to all those other offenders he must rely on before, during, and after the crime event in order to make the contemplated crime possible or worthwhile".

While the notion of co-offending implies a certain amount of collaboration, co-arrests only require the convergence in time and space of two or more individuals who have committed a crime or several crimes. Indeed, in many cases co-offending may be equivalent to co-arrests, although the inverse may not necessarily be true. Many studies employing arrests and even other types of records such as FI cards will refer to the resulting networks as co-offending networks (e.g. Charette & Papachristos, 2017; Papachristos et al., 2015; Papachristos & Wildeman, 2014; Morselli, 2009; Tremblay et al., 2016). In many cases, the relationships observed through police records do not necessarily reflect the collaborative aspect implied by co-offending, even when the records emerge from criminal events. Events such as loitering and drinking in public involve very little collaboration other than being at the same place at the same time. In at least one study using co-arrests networks, the vast majority of offenses involving two or more individuals, and therefore contributing most to the relationships in the networks, are minor offenses such as quality of life offenses, probation violations, and disturbing the peace (Charette & Papachristos, 2017). Furthermore, many of these studies also include informal, non-criminal stops such as FI cards, which may not involve any crime whatsoever.

In a sense, relationships in co-arrest networks may be more similar to Tremblay's notion of co-offending as a "pool of potential co-offenders" (1993, p.20) and somewhat in between the strict definition of co-offending as collaboration in the commission of a crime and the more general notion of delinquent peers. Many studies of co-offending have restricted their study to relationships between individuals who were convicted of crimes with one another or were

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associated to crimes cleared by the police (e.g. Conway & McCord, 2002; McGloin, Sullivan, Piquero, & Bacon, 2008; Carrington, 2009; Schaefer, Rodriguez, & Decker, 2014; Stolzenberg & D'Alessio, 2008). Given the proportion of crimes that never make it to the courts, such data is likely to miss an important number of relationships. The use of arrest records, particularly if minor offenses are included, may increase the scope of the relationships that are included.

The use of arrest records requires researchers to make several assumptions about the nature of relationships observed during arrest events. As Papachristos and Wildeman (2014, p.144) remarked "the underlying assumptions are that people arrested together 1) know each other, and 2) engage in risky behaviors together, in this case, illegal behavior". In addition, one assumption researchers using such data implicitly make is that individuals involved in arrest events are engaged in positive relationships (e.g. friendships) or at the very least, neutral relationships (e.g. acquaintances). It is possible that among the events captured by police records, some relationships may be antagonistic (e.g. two individuals arrested after being involved in a fight) or even involve individuals that do not have a prior relationship (e.g. two strangers involved in a drug transaction). One advantage of using police data is that it enables researchers to construct networks that includes a large number of individuals and events, which would be impossible to do using surveys and observations. The obvious downside is that the larger the dataset, the more difficult it is to come up with precise definitions about the nature of the data we are studying.

Research questions and plan for the remainder of the dissertation

The overarching question I seek to answer in this dissertation is to what extent do networks constructed from police data reflect the variations and biases inherently involved in police work. My goal is to highlight on the one hand the substantial challenges associated with

the extractions of relational data from arrest and FI records, and on the other, to identify potential problems related to the data-generating process behind these data.

Chapter 2 describes the data cleaning techniques involved in the extraction of relationships from arrest and FI records. The sheer size of databases researchers have to deal with brings about unique challenges and presents researchers with several decisions points. However, challenges associated with these data are not limited to the extraction of relationships, but extend to the extraction of attribute data for the individuals involved in these networks. Given the potential use of these data for the study of street gangs, I examine in detail how information about gang membership can be extracted from FI records and discuss the implications for analyses of gang networks.

Chapter 3 examines several sources of variation in police records that are unrelated to the behavior of individuals involved in these networks. Using the City of Long Beach, California as a case study, I explore how changes in police leadership, a reduction of available police officers due to budget constraints, and state-level legal changes may have impacted how police conduct their work and how these issues may be related to variations in the recording of group events from which relational data is extracted.

Chapter 4 considers the influence of a particular type of policy—civil gang injunctions (CGIs)—on the structure of co-arrest and co-FI networks. CGIs are court orders that—among other things—are designed to restrict the patterns of association between gang members within a given geographic area. In this chapter, I test the idea that CGIs have the potential of both influencing gang behavior and the behavior of the police which could in turn influence how social relationships are recorded in police data.

Finally, Chapter 5 discusses the implications of my findings for research on criminal networks using police data and proposes future directions to further investigate whether and in what context we should be using police data for social network analysis.

CHAPTER 2. THE CREATION OF SOCIAL NETWORKS FROM POLICE DATA

Introduction

This chapter describes the datasets used for the remainder of the dissertation. The creation of networks from police data required substantial cleaning and processing before these networks could be analyzed. In the following sections I describe in detail the steps involved in the creation of these networks from arrests and FI data as well as the challenges that I have encountered. Furthermore, by describing the records used for this study, I hope to shed more light on the nature of the networks we are able to observe and potential areas of concern regarding these data. This chapter serves both as a description of the data that will be analyzed for the remainder of the dissertation and the identification of issues that will be treated in the next chapters.

I first describe the content of arrest records and the steps taken to extract both individual level information and relationships. An important aspect of the analysis of these records is to identify the types of crimes that yield group events, as well as the events we might consider excluding. Second, I describe the different methods I have used to extract relationships from Field Interview (FI) cards. The ways FI cards are entered in electronic databases was far less systematic than for arrest records, and therefore required substantial work in order to extract relationships and individual-level information. Third, while the unstructured nature of FI cards created significant challenges for this study, the availability of the data in a raw format presented an interesting opportunity to analyze how information about gang membership is uncovered. I provide a qualitative analysis of the ways officers describe gang members they encounter and the strategies and labels commonly found on FI cards. Fourth, I describe and compare individuals

found in the FI and arrest databases. Finally, I discuss the implications of the observations I make in this chapter for issues related to the definition of relationships extracted from police records, the potential biases related to the individuals included in these records, and outline the different issues I will examine in the next chapters.

Datasets used and the extraction of network data

In the present study, I draw from two data sources: 1) Arrest records, and 2) Field Interview (FI) cards from the Long Beach Police Department (LBPD) collected between 2008 and 2013. Using arrest and FI records, two individuals are connected to one another if they were involved in the same events. Networks extracted from both data sources are what are called two-mode `networks. Two-mode networks are special kinds of networks that include two different types of nodes—in this case, persons and events—for which links can only exist between nodes of a different type. In other words, persons are linked to events but persons are not directly tied to other persons, and events are not directly tied to other events. Although two-mode networks can be analyzed as such, it is not uncommon for researchers to infer links between nodes of the same type based on their shared connections to the same nodes of a different type (e.g. inferring ties between people that share ties to the same events). In fact, most studies using such records do not analyze the two-mode networks, but rather take its projection by multiplying the person by event matrix with its transposed version (event by person matrix).

The decision to study the one-mode projection of a two-mode network is typically guided by two practical concerns. First, although methods to analyze two-mode networks are increasingly being developed, the vast majority of methods to measure and model social network data are still limited to one-mode networks (e.g. Borgatti, Everett, & Johnson, 2013; Latapy, Magnien, & Del Vecchio, 2008). Second, networks created from police data can be very large

and analyzing two-mode networks would typically more than double the number of nodes to be analyzed, which can lead to limitations related to computing power. At the same time, given that the vast majority of arrests are likely to involved one or two individuals, we may not be missing much by analyzing the one-mode projection though this is a question that should be answered empirically. For this dissertation, I will focus on the analysis of co-arrest and co-FI data as it has been the main way these data have been analyzed in the literature and leave the question of whether we should analyze the two-mode network for another time.

Arrest records

   The first source of data used in this study are arrest records. In the current context, an arrest record refers to a documentation of an interaction between an officer and a member of the public where officers had reason to believe that a crime had been committed and led to some sort of consequence for the individual(s) involved such as being placed under arrest or being issued a citation. For this study, I did not have access to further information about what happened beyond the arrests (e.g. formal charges, conviction, dropped charges, etc.). Furthermore, it should be noted that while the dataset includes minor violations such as city code violations, the records do not involve any minor traffic violations (e.g. speeding, traffic signs violation, etc.) other than violation of the vehicle code that led to an arrest (e.g. impaired driving, reckless driving causing injuries, etc.).

   The information available in the arrest database include a unique event-level identifier called the Departmental Record (DR) number, a personal unique identifier called a Master Name Index (MNI), the date of birth, race/ethnicity, and gender of the individual arrested, the time and address where the arrest took place, and the criminal code section referring to the crime believed to have been committed. The DR and MNI numbers are two critical pieces of information for the

purpose of constructing the networks. A DR number is attached to any event that led to an arrest or a citation. Once a DR number is created, it will be attached to any other arrest or citations that occurred during or that are related to the same incident. Thus, in the case of arrest records two individuals who share the same DR number are suspected or known to be connected to the same criminal event. The MNI number is assigned to any new individual encountered by the police department. The same number was used in the FI records, allowing us to match individuals from both datasets.

The arrest dataset includes 171, 336 person-arrest records and 145, 610 unique events (DRs) between 2008 and 2013. In total, the events in the arrest dataset include information about 89,904 unique individuals. On average, individuals were involved in 1.89 arrest events (SD=2.97) and the median person was involved in 1 event. Figure 2.1 shows the highly skewed distribution of the number of arrest events per individuals. The vast majority of individuals (71.6%) were arrested only once between 2008 and 2013, 13.2 % were arrested twice, 5.4% were arrested three times, and 9.8% were arrest 4 times or more. Even though the x axis of Figure 2.1 ends with a category combining individuals with 15 or more arrests, it should be noted that the maximum number of arrests in the dataset is far greater than 15—the individual with the largest number of arrests in the dataset was part of 183 events during the study period. In fact, 670 individuals had 15 or more arrests, with 40 individuals having 50 or more and 4 individuals with 100 or more arrests. The shape of this distribution and its extreme values speaks to the variation in the kind of individuals that we can find in these records. I will return to this observation and what it means for the interpretation of the network created from arrest records in the discussion section of this chapter.

The arrest events can be classified by type of crime. I classified criminal codes found in the arrest database into 8 categories: 1) Violent, 2) Property, 3) Drug, 4) Gun and weapons, 5) Vehicle, 6) Probation and Parole violations, 7) Quality of Life (QOL)[1], and 8) Other[2]. Since multiple arrests can make up an event—such as when multiple individuals are arrested for different crimes in the same event or when a single individual is arrested on multiple charges—I classified each event by the most serious crime category in each event, as listed above. Only 4% of arrest events had multiple crimes falling in different categories. Figure 2.2 shows the distribution of events by crime category. By far the most frequent crime category is QOL with 34.7% of all events, followed by Drug related-crimes at 14.4%, Other crimes at 13.3%, Violent crimes at 11.8%, Vehicle offenses at 11.0%, Property crimes at 8.3%, Probation and parole violation at 4.7%, and Guns and weapons violations at 1.9%.
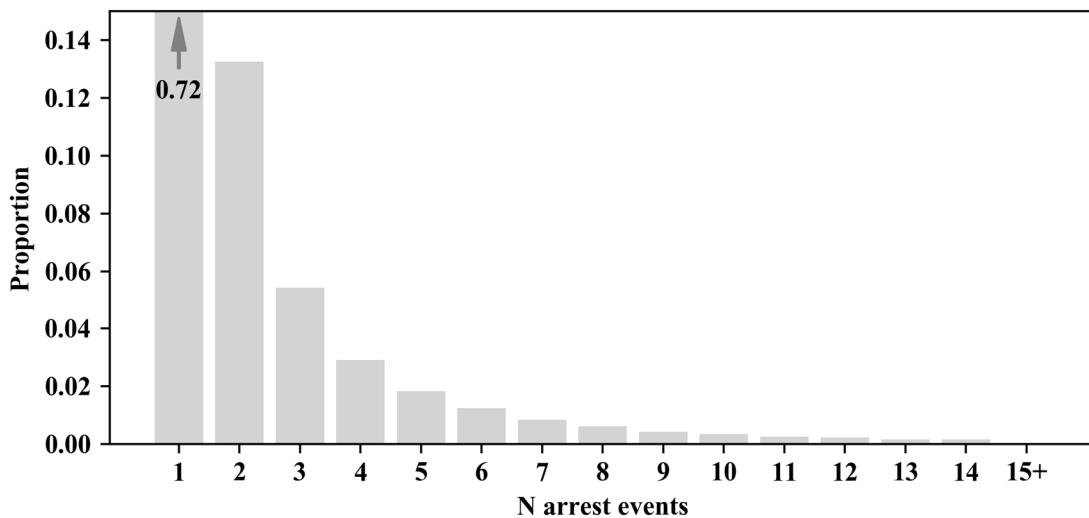
Figure 2.1. Distribution of the number of arrest events per individuals

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[1] QOL include offenses such as loitering, drinking in public, curfew violations, public nuisances, truancy, trespassing, bicycle and pedestrian violations, destruction of property (graffiti, possession of tools for graffiti), and fare violations.
[2] Other crimes include offenses that could not be classified in other categories such as forgery, fraud, offenses related to prostitution, obstruction of police work, non violent sexual offenses, extortion, embezzlement, child neglect, and miscellaneous violations of city and business codes.

Arrest events involving QOL offenses, and to some extent drug-related crimes, are likely to differ in important respects from other types of events. First, such crimes are perhaps more likely than others to be directly observed by officers. Whereas arrests for more serious crimes such as robberies, homicides, and thefts are more likely to be executed after the crime has been reported and investigated, arrests for QOL offenses may be more likely to be conducted while patrolling or responding to a call for service. Therefore, the recording of these crimes may be more likely to be influenced by changes in the way police resources are allocated. Second, given the more minor nature of QOL offenses and some drug-related crimes (e.g. minor possession) whether or not crime of this nature leads to an arrest or citation may be more likely to involve officer discretion. As I will show in the next section, QOL and drug-related crimes appear to be more "social" crimes, and the source of many ties for our networks. Therefore, whatever affects the enforcement and recording of these types of crime will likely have an important impact on the relationships we are able to extract from arrest records. I will examine QOL offenses and drug-related crimes more closely in the next chapter.
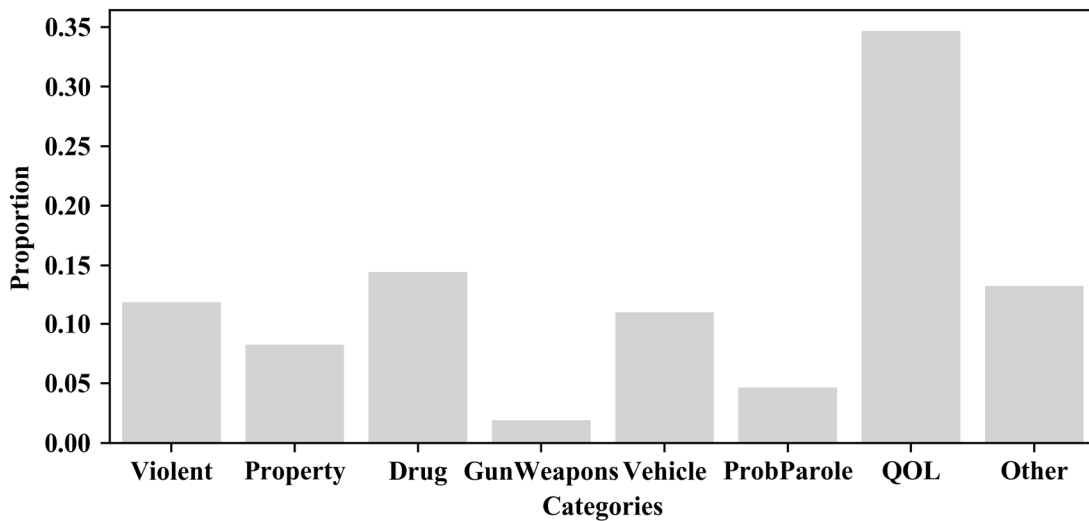
Figure 2.2. Proportion of arrest events by crime category

A relationship in the co-arrest network is inferred from two individuals being associated with the same event. The average arrest event involves 1.21 individuals (SD=0.81). Of all arrest events, 85.94% involve only one individual, 10.37% involve two individuals, 2.23% involve three individuals, 0.73% involve four individuals, and 0.73% involve five or more individuals There are a handful of unusually large events that deserve some attention. There are 60 events that include between 15 and 44 individuals. Prior studies using similar data exclude events that involve a large number of individual. For example, Schaefer (2012) excluded events with a high number of participants (more than 12). Schaefer (2012) argued that inferring ties from events that include a large number of individuals violates the basic assumption that co-participation in an arrest event reflects a prior social relationship.

A closer look at these larger events reveals that Schaefer's reasoning was probably correct. Of the 60 events that involved more than 15 individuals, 48 (80%) were events where the most serious crime committed was a QOL offense, most often involving offenses related to fare violations on the transit system. Indeed most of these events are located along the major transit line in Long Beach. The remaining events tend to be located either at major public landmarks (e.g. City Hall, the Public Library) or parks and beaches. For instance, 10 events were located around a complex that houses the public library and City Hall—which is a location known as a gathering place for homeless people of the city. At least one event was the result of a protest, and 2 others were located at a skate park in North Long Beach where several skateboarders present were issued violations of city ordinances requiring that they wear helmets.

The vast majority of events involving an unusually large number of individuals typically reflect singular targeted operations by the police (e.g. displacement of homeless individuals, crackdown on safety gear) or events involving the public gathering of a large number of

individuals (e.g. protests, parties). While these events might bring together individuals who actually know one another, it would be a stretch to assume that *all* individuals know everyone else present. For those reasons, I employ a strategy similar to that employed by Schaefer (2012) and removed events with more than 15 individuals involved.

Table 2.1 describes the size of events by crime type. On average, QOL events produce the largest events, and Vehicle and Probabtion/Parole events have smaller events, though the differences between crime types are not very large. When we consider the percentage of events with multiple participants, QOL, Drug, and Property crimes are more likely to involve two or more individuals. The uneven distribution of events by crime type combined with differences in the sizes of the event for different types lead to even larger discrepancies when we consider the number of ties each crime type contributes to the co-arrest network.

Table 2.1. Size events by crime type

	Mean (SD)	% solo	% 2 +	% 2 indiv	%3 indiv	% 4 indiv	%5 +
Violent	1.20 (0.63)	86.05	13.95	10.20	2.44	0.82	0.50
Property	1.23 (0.59)	82.28	17.72	13.96	2.78	0.57	0.41
Drug	1.24 (0.62)	82.10	17.90	13.68	3.01	0.77	0.44
Guns /Weapons	1.21 (0.59)	84.46	15.54	11.39	3.21	0.56	0.37
Vehicle	1.05 (0.29)	95.71	4.29	3.68	0.41	0.12	0.08
Probation /Parole	1.09 (0.38)	92.37	7.63	6.37	1.03	0.17	0.06
QOL	1.29 (0.89)	82.40	17.60	12.33	2.75	1.14	1.37
Other	1.12 (0.50)	91.68	8.32	6.39	1.25	0.35	0.33

Table 2.2 breaks down the ties that make up the co-arrest network by the crime type of the events from which they are extracted. QOL offenses contribute the vast majority of ties (56.14% of all ties) in the co-arrest network, with drug arrests being a distant second category with 13.81% of ties. Clearly, any process that would affect the enforcement and recording of QOL and Drug offenses will have an important impact on the structure of networks extracted

from these data. I will return to this point in the discussion as the analysis of QOL and Drug

offenses will be important in the next chapter.

Table 2.2. Number of ties by crime type

	N ties (% total)	N unique ties (% total)
Violent	5,283 (10.69)	5,253 (10.69)
Property	3,680 (7.30)	3,623 (7.37)
Drug	6,962 (13.81)	6,900 (14.05)
Guns/Weapons	801 (1.59)	799 (1.63)
Vehicle	1,060 (2.10)	1,060 (2.16)
Probation/Parole	818 (1.62)	816 (1.66)
QOL	28,307 (56.14)	27,168 (55.31)
Other	3,507 (6.95)	3,504 (7.13)
Total	50,418	49,123

Another category that deserves additional attention is the third most common category,

violent crimes. As I have discussed in the prior chapter, part of the assumptions involved in the

creation of co-arrest networks is that the ties observed in the networks involve positive

relationships (e.g. friendships), or at the very least neutral relationships (e.g. acquaintances) that

may influence criminal involvement in some way. Ties arising from violent incidents raise the

specter that some of these relationships may in fact be antagonistic in nature. For example, two

rival gang members involved in a fight may be arrested as part of the same event. The data

available does not allow us much insight into the context of arrest events which would be

necessary to examine whether these ties are antagonistic or not. Of course, this could be true of

any crime type. For instance, two individuals who do not know one another or are rivals could be

involved in an arrest event because they were caught during a drug transaction. However,

relationships based on violent crimes may be more likely to generate antagonistic ties.

The only way to assess the possibility that some of these ties may be antagonistic

relationships is to examine events that involve gang members. Of the 16,258 violent events,

2,305 of these events were group events, including 1,103 involving at least one gang member. Of

those events, 549 events involved at least 2 gang members, with 275 events where all pairs of gang members involved in the events were members of the same gang. This leaves us with 274 events where at least two different gangs were involved. Unfortunately, I was not able to obtain information about rivalries between gangs in Long Beach so it is difficult to assess whether these relationships are in fact antagonistic; some gangs may be allies. If we are to assume that all violent ties between members of different gangs are in fact antagonistic, the 477 such ties would make up 0.97% of all ties in the co-arrest network.

FI records

The second source of data used in this study comes from FI cards. FI cards are physical cards filled out by officers during interactions with members of the public. These cards are used to document a wide variety of interactions but most commonly they are records of encounters that arise during the investigation of a crime or suspicious activity. FI cards include information about the encounter such as the date, time, and address where the stop occurred, as well as information about the individual(s) present during the stop such as residential address, date of birth, race/ethnicity, gender, gang membership, and a short description of the encounter.

The process of digitally recording information collected through FI cards is far less systematic than for arrest records, and therefore the identification of events is not as straightforward a task as using a DR number or another unique event identifier. The process of documenting and recording FI cards goes as follows: First, officers fill out physical cards while out on patrol, then bring the cards back to the precinct. If a clerk is assigned to the task, they are entered in the system. If no one is currently assigned to the task, the cards are kept until someone is assigned to enter them. This change leads to some inconsistencies in the way the data is entered and the form of the information that was ultimately available to me.

While the information in the cards is divided into many separated fields, most of the fields are not kept separated when the information is entered into the database. Most of the fields except for the date of birth, gender, race, date and time of stop, location of stop, and the name and MNI of the person stopped are all entered in a single field called "Narrative".

While the cards themselves were designed to be records of incidents, officers of the LBPD typically will fill an FI card for each individual present during the stop. Unlike arrest records, there are no event-level identifier that allows me to recreate the events and therefore link individuals through their co-presence at an FI stop. The "Narrative" is a field where all the remaining information captured in the card is entered. Typically, this includes information about the circumstances of the stop, information about the probation or parole status of an individual (e.g. conditions, probation/parole officer name), physical description of the individual, school where the person attends, employer, etc. More importantly for my purposes, it also includes information about other individuals involved, and about gang membership.

The unstructured nature of this data makes it difficult to extract information. In many cases the narrative includes brief descriptions of the events and individuals involved. Below are typical examples of the kind of information included in the unstructured narrative:

"Pedestrian lives with girlfriend [Name] in Panorama City. In area visiting "homies". Parole for 10851vc previous employer: Walgreens tools   Cota/Pch,Lb clets: aesh   Record Type: Cdc Idn: Xxxxx   Fcn: Xxxxxxxxxxxx" (Example 1)

"925 Subj Possibly Contacting Young Girls In Park Playground" (Example 2)

Example 1 is a FI card that was completed during a pedestrian stop and includes information on where the individual lives as well as information about employment and parole status. It also includes codes returned by the California Law Enforcement Telecommunication System

(CLETS), California Department of Corrections (CDC) id number, and a File Control Number (FCN) used to generate the search of the Criminal Justice Information System (CJIS).

FI cards also include common codes used by officers as shorthand for certain situations. For instance, in Example 2, "925" is a shorthand commonly used by officers to signify suspicious behavior. It is often used in combination with other terms such as "925 gang member" (suspected gang member) or "925 drug sales" (suspected drug sales). It is also common for officers to use codes such as 5150 to refer to mentally ill individuals even when no involuntary psychiatric hold is carried out[3]. Officers sometimes use "5149 ½" to indicate that someone shows some signs of mental disorder that do not meet the criteria for involuntary psychiatric hold.

In order to create FI events we must link together FI cards that were filled out following the same stop. Unlike for arrests, FI cards do not have a DR number linking individuals to an event but instead, each record is a person-event record. Even though there is a field on the FI card to write down the information of other individuals present, officers often write a separate card for each individual involved. Furthermore, the way cards are transferred in an electronic format is inconsistent. Most commonly, the officer entering the information in the computer will create a new record for each individual mentioned in the card. However, in some cases the card is entered with the name of other individuals involved within the narrative field as in the examples below:

" Subj w/2 other subjs ([NAME], 05/10/93, & [NAME], 03/12/92) Subj's hair: Buzz cut. Probation for 289PC (#XXXXXX) Subj stopped w/2 Ghetto Boys gang members. No Supervised Release Records" (Example 3)

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[3] 5150 is the section of California's Welfare and Institutions Code which allows officers to involuntarily detain a person suspected of having a serious mental disorder

"Location of Contact - The Rear of listed address. Gang aff: 9th St Cocos Moniker: [Moniker] (Jain #XXXXXX) Tattoo: 3 Dots - R.wrist. 9th St are Surenos. FI'd w/ [NAME] from 9th St Locos. Self admit gang member - jumped in by [Moniker] a couple of months ago." (Example 4)

Extracting the names of individuals from within the narrative field is a challenging task in and of itself, but more difficult is the task of matching these names to the unique identifiers (MNIs, or Master Name Index) assigned to them by the police.

Thankfully, the extraction of names of other individuals involved in a FI stop from the text of the narrative can be simplified by identifying common patterns in how such information is entered. One of the most common ways this information is entered in the database is similar to Example 3 above. This was accomplished using regular expressions (regex), a special feature of many computer programming languages such as JavaScript and Python which allows the identification of text by describing regular patterns surrounding the text one wishes to extract. For example, the names in Example 3 would be found using the following regex:

(?:person|subj|subject|subjs|subjects)\s*(?:w\/|with|w\s)(.*)

This expression searches for the strings 'person' or 'subj' or 'subject' or 'subjs' or 'subjects' ((?:person|subj|subject|subjs|subjects)) followed by 0 or more spaces (\s*) followed by the strings 'w\' or 'with' or 'w '(?:w\/|with|w\s) and returns any following sets of characters (.*). This approach is flexible enough to identify sections of the narrative that may contain names of individuals present even if these sections do not always use the exact same words or have typos in them. Once these sections are identified I used a similar approach to extract names and dates of birth since these pieces of information tend to follow predictable patterns. Once extracted the names and date of birth were compared to the lists of names and date of birth identified in their own fields in other arrest and FI records to find potential matches. Because cards are hand written by officers, then interpreted and typed in the computer by another officer or staff later,

matching was done using fuzzy string matching. Fuzzy string matching is a technique that evaluates how different two strings are to one another mathematically.

Using the Python package FuzzyWuzzy (v.0.15.1), names identified by the procedure described above were compared against a bank of names from other arrest and FI records using the Levenshtein distance to calculate the differences between the names. The Levenshtein distance compares two strings and evaluates how many edits it would take for two strings to become identical. The package FuzzyWuzzy normalizes the distance by dividing the distance by the maximum possible number of edits and returns a percentage that can be interpreted as the similarity percentage. Names matched at 80% or more with the same date of birth were matched and assigned the MNI number associated with the name in other records. As I explain below, a similar strategy was employed to identify specific gang names found in the narratives.

In total, 3,636 names were identified using this strategy and 88.61% of those names could be matched to a MNI number in other databases. Typically, names that could not be matched were either incomplete (only the first name initial) or no date of birth were provided. In those cases, unambiguous matches with other names could not be achieved and the names were dropped. Once the procedure was completed, all names were purged from the dataset to maintain the anonymity of individuals in the dataset.

The main strategy to create FI events was to group cards based on the date, time and location listed. Since officers fill out FI cards manually there are a lot of inconsistencies in the addresses and exact time listed. First, I had to establish a time threshold to match the FI cards. In order to identify the proper threshold, I examined arrest records for events that are closest to the typical FI stop: QOL offenses. Since arrests records are linked by a DR number, each individual arrests has its own date and time recorded by an officer. By examining the differences in time

between individual arrests for QOL offenses grouped together under a single DR number, I obtained a distribution of the time gap between recorded times within each arrest event. The average time difference within QOL arrest events is 15.86 (SD=96.61), with 78.60% being less than 10 minutes and 88.73% being 15 minutes or less. This distribution was remarkably similar to the findings of the 2011 Bureau of Justice Statistics' survey of Police-Public Contact Survey, where 70.28 % of respondents indicated that their police encounter during a street stop lasted 10 minutes or less, and 81.13% indicated that their encounter lasted 15 minutes or less. Therefore, I use 15 minutes as a conservative threshold to match FI cards.

Next, I had to decide on a distance threshold to match cards belonging to the same event. Obviously, the easiest cards to match are those that have the exact same addresses. Of the 35,406 pairs of cards that fall within 15 minutes of each other and within a distance of 1 mile, 72.80% of pairs have a spatial distance of 0. However, restricting the distance threshold to those that have the exact same location would be too conservative. For instance, officers filling out the cards may take down the exact street address on one card, while they will note the street corner on another. Unfortunately, it is not possible to use the same strategy used above to identify the time threshold because only the first address associated with an arrest event was geocoded. Instead, I examined the distribution of distances within a plausible range of distances (less than a mile radius).

I also calculated the average length of a street block in Long Beach. This allowed me to estimate the average distance between a street corner and another point found on the same block (i.e. a specific street address). The average perimeter of a block in Long Beach is 696.76 (SD=785.29) with the first quartile falling at 411 feet, the median at 598 feet, and the third

quartile at 773 feet. Ultimately, I opted to set the threshold for distance at 500 feet, which is slightly more conservative than the median block perimeter.

Once events falling within a 500 feet radius and a 15 minutes time difference are collapsed together, we can create another kind of event that matches FI cards to the arrest events we have created. Using the same strategy used to match FI cards to one another, I matched the newly created FI events as well as the remaining FI cards that were not matched to other cards. Officers will sometimes begin by conducting an FI stop, and upon further investigation, decide to arrest some or all of the individuals present during the stop. This strategy should allow for both the identification of new multi-person events and of additional individuals involved in a given stop but that are arrested. Finally, since it is not uncommon for FI cards to be created at the same time as arrests are made, I matched the identified FI events to the arrest events using the same strategy used for the pairing of FI cards.

In total, matching based on the time and location of FI cards led to the creation of 9,803 FI events (Table 2.3). For 940 of these events, I was able to extract names from the narratives of the cards that made up these events. In many cases, matching cards based on time and location had already captured the names. For 146 of these events, extracting names from the narratives led to the addition of at least one new individual to the event. Similarly, I was able to match 1,035 FI events to an arrest event. Of those, 319 led to the addition of at least one new individual to the FI events. For 93 FI events, both names and arrests were matched, though only 15 led to the addition of new individuals. Finally, the name and arrest matching strategies led to an additional 1,886 FI events with more than one individual. Event ids were created for each card that was not matched or did not have names within the narratives for a grand total of 58,474 FI events—11,698 involving 2 or more individuals, and 46,785 involving a single individual.

Table 2.3. FI event creation process

	Events	Unique Contribution
FI card matching-Time+Distance (TD)		
TD only	7,921	9,353
TD+Arrests	942	304
TD+Names	847	131
TD+Names+Arrests	93	15
Total TD		9,803
Additional events		
Names		769
Arrests		1,051
Arrests+Names		66
Total added		1,886
Total multi-person events		11,689
Total single-person events		46,785
Total FI events		58,474

Extracting information about gang membership

FI cards vary in terms of the level of information that is recorded about gangs and gang

membership status. FI cards are important tools used to document gang membership, which is

particularly helpful in order to serve gang injunctions. However, the identification of gang

membership in FI cards is done rather haphazardly. In this section, I demonstrate using examples

from FI card narrative the various strategies LBPD officers use to document gang membership.

At times officers will note incredibly detailed information about gangs noting the specific

clique of membership, how long ago an individual joined the gang, the initiation method, the

length of the initiation, who was involved in the initiation, etc. (see Examples 3 and 4). It is also

not uncommon to observe that some members become affiliated to the gang through family ties

and to note specific identifying features of specific gangs such as tattoos or, as in example 5,

baseball hats which are a common identifying features of many gangs in Long Beach and in

surrounding areas.

"Gang: el monte hicks. Jumped in when he was 12-1/2 yrs. Jumped for 13 seconds by [moniker], [moniker] and [moniker]. Hood was created in 1950's. Arrested for 422/243(e)(1), did time saledad in "a" yard, put in work for south siders. Dr# 11-49768, call #1651. T15-2102." (Example 3)

"riding BMX bike through alleys. had fake chrome 44 magnum in waistband. said it was for protection from ICG. said he was jumped into "kurrupt individuals" and goes by "[MONIKER]". says it is a Long Beach gang and is 135 members strong. said they have beef with 2FE. gang affiliation - KI "kurrupt individuals" hair slicked back" (Example 4)

"Stopped for 27007VC. His family from "SOS". Subject driving in Long Beach with a Seattle Mariners baseball hat which represents Sons of Somoas. And a "S" belt buckle." (Example 5)

Generally though, gang-identifying information can be divided into four types: 1) the "walks like a duck" strategy, 2) the "guilt by association" strategy, 3) the gang box strategy, and 4) the "self-admit" strategy.

The "walks like a duck" strategy is a very commonly used tactic to identify gang membership. As the name suggests, the officer's rationale for assuming gang membership in those cases can be summed up by the adage "if it walks like a duck, and quacks like a duck, then it must be a duck". For instance, in example 6 the officer remarks the gang "attire" and the fact that the stop was made in a gang area. What makes these types of narratives difficult to interpret is that they rarely go beyond these observations. It is difficult to interpret whether officers simply expressed suspicion over membership, or were using these observations as providing evidence of membership. In other cases, officers will use these observations to question an individual's claim of non-membership such as in Example 7. Officers also use their knowledge of common identifying features of certain gangs such as wearing logos of specific professional baseball and football teams to validate whether their assumptions are correct. The narrative of Example 8 highlights such a situation where an officer suspecting that an individual was member of the Rollin 20 Crips gang—who commonly use Pittsburgh Steelers gear as an identifying feature—

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tries to figure out if the individual knows any players on the team, presumably to differentiate

between Steelers fans and Rollin 20s members.

"bicycle stop. riding on sidewalk. cited. gang attire in gang area with recent shootings."
(Example 6)

"Walking across street on red with white subject dressed like a gangster. Said he was no longer
active, but he was totally dressed down like a thug. Also showing his tattoos." (Example 7)

"Ped stop. Gang logo for steelers and "c" on bb-cap for crip. Gang area. Doesn't know any
steeler or cincinatti players" (Example 8)

The "guilt by association" strategy refers to situations where an officer will infer

membership for a given individual based on the fact that the stop also involved known gang

members. It is difficult to clearly identify when such a strategy is used because it can easily be

confused with instances where an officer is providing a thorough assessment of membership by

differentiating between members and affiliates. It is clear that some officer have a much more

sophisticated understanding of gang membership and recognize membership as falling along a

continuum rather than falling neatly in the member/non-member category (see Example 9)

However, it is difficult to understand whether officers use terms such as "associate", "affiliate",

and "member" interchangeably or whether they intend their use as designating levels of gang

involvement. Consider Examples 10 and 11. The FI card in example 10 was filled out during a

traffic stop that involved several Asian Boyz gang members. The fact that the officer states that

"he does not claim gang *affiliation* but *associates*" suggests that by "affiliation" the officer

actually meant membership. Furthermore the language of the narrative of Example 10 does not

allow us to distinguish whether the individual volunteered the information about his

"association" with the gang or whether the officer simply inferred association from the situation.

Example 11 is similar to example 10, but where the individual denied "membership" but the

officer nevertheless gave the individual the label of Playa Larga "associate".

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Conversely, Example 12 shows an officer noting a distinction between membership and associating, and because the officer writes that the subject "admits" association, it suggests that the association was not simply inferred from the situation but that the individual himself recognized his status as an "associate". Example 13 gives slightly more context the use of the term "association" by explaining that the individual admitted association to East Side Longo through his life long friendship with two well-established members of the gang.

"Says he got jumped in a year. More of a Pooh Butt Periphal. says on 211 probation, but on probation 10851 CPT. Hangs w/ K.A.K. "Known As Kings". Mom is cooperative/clueless. Osgood Block Locos. Gang: Lynwood 13 Mon: Goofy Bike: BMX, blk, Mongoose on tire Hair: Slick back" (Example 9)

"subject was the rear passenger in the above vehicle. he does not claim gang affiliation but associates with asian boyz" (Example 10)

"PL assoc. Location: rear of 730 lime ave.subj detained drinking alcoholic bev. In the alley. Subj. Denies gang membership but associate w/ PL gang member. Subj. Build: heavy" (Example 11)

"Gang: blvd mafia lives in carmalitos, stopped w/2 blvd crips, doesn't claim member, but admits assoc" (Example 12)

"Admits association w/ ESL gangsters. Was hanging out w/ 2 of them. Said they were life long friends. Going to his truck when we detained him" (Example 13)

The gang box strategy refers to the practice of filling out the gang information without any context about how it was revealed. An advantage of this strategy from a data extraction standpoint is that it is clearly identified within the narrative. For instance, the narrative of Example 14 includes a field named "Gang:" followed by the gang of membership. In that sense, the gang box strategy provides us the same level of information available from arrest data, where no context is given for the definition of gang membership. In some cases, officers will use this strategy to indicate that a subject refused to provide their gang information (Example 15), or

sometimes will indicate that the individual was not a gang member by simply writing "None" next to the field.

"Sub was cited for driving w/no license. The listed sub was with him. gang: ESL 15th st" (Example 14)

"Probation for court order violation. 925 call/suspect. Gang: Refused Mon: Refused (No hits on probation.)" (Example 15)

Finally, the "self-admit" strategy appears to be the most common strategy for defining gang membership. This strategy is one that appears to be most consistent with the self-report method used to establish membership in traditional survey research. Examples 16 and 17 are typical narratives from uses of this strategy. One of the reasons why officers often make a point of noting whether an individual "self-admits" membership is that they recognize that this constitutes a much more solid legal basis when used in court compared to assessments based on dress and tattoos. Curiously, it is not uncommon to find narratives that include such circumstantial evidence of gang membership even when a member "self-admits" membership. For instance, Example 16 provides information on gang tattoos, attire, and the fact that the stop occurred in a gang area. This type of "overkill" is commonly used in FI cards. At times, it appears as though officers are filling out a "Tattoo-Attire-Area-Associate-Admits" checklist when filling out the cards even though no such list is present on the physical card (see Example 18). Ironically, while officers note all sorts of identifying features of members, it is also common for them to fail to record any specific information regarding the specific gang of membership. Whereas the narrative in example 16 specifies both the gang (ESL) and the clique (Barrio Viejo Clique) to whom the subject belongs, examples 17 and 18 simply indicate gang membership.

It is possible that officers more knowledgeable about gangs are using these attributes to establish levels of membership. Gang officers indicated that there was no official criteria used

department wide to establish membership. Again, since officers are often asked to testify in court regarding establishing gang membership, it is possible that some officers prefer to provide a preponderance of evidence in order to be able to dismiss any doubts regarding membership.

Another reason for the common use of the "self-admit" method is that, according to LBPD officers, gang members are surprisingly forthcoming when it comes to divulging their gang membership. While many refuse to provide this information and others appear to be either lying or downplaying their association (according to officers), gang members either seem to be well aware that law enforcement keeps records of such information and see no point in hiding it from officers or are simply proud to represent their gang. In fact, in a few occasions, officers will note that a subject will admit that she can be found in LBPD files as a documented member but will attempt to correct the information (as in example 19). At other times, officer will actually use the information they have on prior contacts with a given subject to challenge their claim that they are not involved in gangs. For instance, example 20 shows a situation where a subject initially denied membership only to admit to gang membership when "presented with overwhelming evidence".

"Self admit East Side Longo gang member, contacted in gang area, has gang tats and attire, gm ESL-VIEJO clique" (Example 16)

"Self admitted, gang tattoos, attire and location." (Example 17)

"Contacted in a gang area. Subj. is an admitted g/m with gang tats. Subj. stated he was jumped in at 13 yrs. old by [Moniker], [Moniker], & [Moniker] at Henderson/Cowles." (Example 18)

"Subj contacted consensual encounter. Admitted to long history of being arrested stated he was "in gang file" but isn't a member. He only "hangs" with CBC. No moniker listed" (Example 19)

"Subj found loitering in marina after hours. Subj on parole for 212.5(c)pc - documented baby insane. Extremely uncooperative. Clothing and tattoos reflect gang membership with baby insane crips. Denied membership at first, later admitted when presented with overwhelming

evidence; pedestrian. heavily tattooed. on parole 212.5(c)pc. facial feature: thin beard."
(Example 20)

Coding strategy

The observations above about the variability and inconsistencies in the identification of

gang members during FI stops posed great challenges to the coding process. From a practical

standpoint, a detailed coding scheme would be extremely onerous given the size of the dataset.

That said, it was difficult to clearly identify gang membership in much detail given the

inconsistencies with which the data is recorded. To identify cards that could potentially include

gang membership information, I searched for several keywords such as "gang", "admit" and

"member". Of the 72,920 FI cards, 23,220 (31.84%) included at least one of these keywords,

including 21,050 (28.87%) that included the word "gang". Of course, simply because the word

"gang" is included in the narrative of the FI card does not necessarily indicate membership. As

we have seen above, it is not uncommon for an officer to note the presence of gang associates or

suspect that an individual's tattoos are gang-related, even though it is doubtful that the individual

stopped is actually a gang member. Furthermore, in some instances the word gang is present in

the narrative to indicate that an individual is *not* a gang member.

Whenever an individual stopped self-admitted to be a gang member, I automatically

coded this individual as being a gang member. In many cases, FI cards did not describe the

circumstances leading to the identification of gang membership. For those cards, gang

membership was assumed if the narrative specified that the individual was a gang member, or if

the narrative reported a specific gang of membership. I was careful to code as non-gang members

individuals where it was specified that the individual associated with gang members but was not

a member, or where the officer restricted his assessment of membership based on the location of

the stop, the clothing style of the individual, or the fact that other members were present at the stop. In total, I identified 8,377 gang members in FI events, or 21.76% of individuals in FI cards.

Since the arrest data also has a gang membership field, I combined both the labels from the arrest data and the FI data to create the final gang membership measure. When adding information from the arrest data, the number of gang members found in the FI data is 9,490 or 24.64% of individuals in FI cards. Having gang membership information from two sources allows us to assess how well the labels converge. Of the 6,903 individuals identified as gang members in either database (that were arrested *and* FI'd between 2008 and 2013), 49.48% were identified as gang members in both the arrest and FI data, 15.9% were identified as gang members in the arrest data only, and 34.59% were identified as gang members in the FI data but not the arrest data.

Clearly, the fact that almost 1 in 4 individuals in FI stops can be labeled as gang members reinforces the notion that FI cards are often used to identify and document the activities of gang members. The discrepancies between the arrest and FI gang labels could also be interpreted as evidence that the use of FI cards is a more effective tool to identify gang membership. It could be that the informal nature of FI cards makes gang members more comfortable to divulge their gang status than if they are faced with an arrest where admission of gang membership could lead to additional penalties or open up the prospect of a longer sentence.

Alternatively, it could also indicate that police officers are less thorough in their assessments of gang membership. As I have outlined above, strategies such as the "walks like a duck" or "guilt-by-association" may cast a wider net than is appropriate and thus labeling individuals in FI cards as members when they really are not. Even if I was careful not to label individuals as gang members in such cases, there still remain a non-trivial proportion of

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individuals who are only labeled as gang members in the FI data. Of course, it is entirely

possible that the discrepancies are simply the result of a time difference between an FI and an

arrest, where an individual joined a gang after being arrested or FI'd. However, if that was the

case we would see a similar proportion of cases where individuals are labeled as members in the

arrest but not the FI data. Furthermore, it is rather interesting to note that 2,587 gang members or

27.26% of gang members in FI data, were never arrested (in Long Beach) during the study

period. Given the well-established relationship between gang membership and criminal

involvement, it is surprising to find such a large proportion of gang members that never even

received a citation during the study period. While it is likely that some of these individuals were

simply criminally active prior and after the study period or were arrested outside of the LBPD's

jurisdiction, it could also be that these individuals are in fact mislabeled by the police

department.

Individuals in arrest and FI records

Table 2.4 describes the individuals that make up each of the event databases. The arrest

events include 89,904 individuals while the FI events bring together 38,503 individuals. Several

differences between the two databases are worth pointing out. Individuals in the FI data appear to

are slightly younger, more likely to be male, and far more likely to be a gang member. It is not

appropriate to conduct any statistical test to examine whether these differences are statistically

significant because a substantial proportion of the arrest sample and FI sample overlaps (more on

this below). That said, Table 2.4 suggests that FI cards are a tool of choice for police officers to

identify gang members.

Table 2.4. Description of individuals in the arrest and FI records

	Mean (SD)	Median	Min	Max
Arrests				
N=89,904				
Number of events	1.89 (2.97)	1	1	183
Age at first event	31.46 (13.14)	28	10	101
Fis				
N=38,503				
Number of events	1.93 (2.55)	1	1	51
Age at first event	29.84 (12.90)	26	8	95

	Percent	
	Arrests	FIs
Gender		
Male	75.44%	82.46%
Female	24.41%	18.70%
Missing	0.15%	0.00%
Race		
Black	30.21%	33.48%
Hispanic	40.71%	36.99%
White	20.91%	20.08%
Other	6.47%	5.75%
Missing	1.71%	3.70%
Gang Membership	10.25%	25.01%

A comparison of the age at first event (within the 2008-2013 period) distribution for FI

and Arrest events is plotted in Figure 2.3. Compared to arrest events, a larger proportion of

individuals tend to be part of an FI stop in late adolescence and in their early twenties. This may

be a function of the tendency of FI stops to involve more gang members than arrest stops since

gang membership tend to be more prevalent for this age range (e.g. Klein & Maxson, 2006;

Thornberry, Krohn, Lizotte, Smith, & Tobin, 2003). Alternatively, it could reflect a tendency of

officers to use more discretion with juveniles, letting them off with a warning documented on an

FI card rather than arrest them or issuing a citation.

Given the demographic composition in Long Beach, it is apparent that African

Americans are over-represented in the data. According to the 2010 census, the population of

Long Beach is composed of 13.0% African Americans, 42.4% Hispanic, 27.7% white, and

16.9% mixed and other races and ethnicities. The over-representation of African Americans is slightly higher in the FI data compared to the arrest data. Another group that appears to be more likely to be targeted by FI stops compared to arrest records are males. It could be that, as I argued above about age, that the difference is due to the over-representation of gang members in the FI data since only 6.85% of gang members in the data are female.
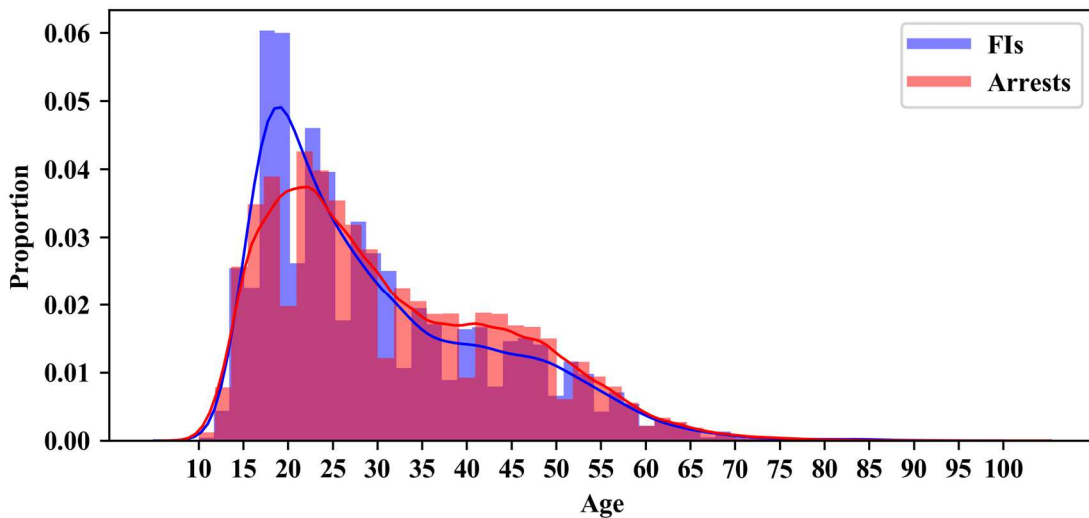
Figure 2.3. Distribution of age at first event for FIs and Arrests

Table 2.5 provides the description of the combined sets of individuals from both datasets and those found in arrest and FI events only, as well as those that can be found in both. When individuals found in both the arrest and FI datasets are combined, we find a total of 109,585 individuals; 65.00% were only arrested, 17.96% were only FI'd, and 17.04% were both arrested and FI'd during the study period. This tells us that the majority of individuals (51.31%) in the FI data have not been arrested in Long Beach during this time period. While some of these individuals might have been arrested before or after the study's time period or outside of LBPD's jurisdiction, this observation suggests that the use of FI cards casts a much wider net than is probably necessary for crime prevention purposes. To be sure, FI cards are used in a variety of

situations and for various purposes such as during investigations as an intelligence-gathering tool thus we should not expect everyone present to at an FI stop to be criminally involved.

Table 2.5. Characteristics of individuals by datasets

	All	Arrests Only	Fis Only	Arrests+Fis
Number of individuals	109,585	71,231	19,681	18,673
Number of arrests				
Mean (SD)	1.55 (2.79)	1.37 (1.19)	--	3.91 (5.66)
Median	1	1	--	2
Number of Fis				
Mean (SD)	0.65 (1.74)	--	1.17 (0.68)	2.70 (3.39)
Median	0	--	1	1
Number of Fis+Arrests				
Mean (SD)	2.20 (3.79)	1.37 (1.19)	1.17 (0.68)	6.55 (7.46)
Median	1	1	1	4
Age at first event				
Mean (SD)	31.21 (13.19)	32.16 (13.25)	30.35 (13.30)	29.30 (12.48)
Median	28	29	26	26
Gender				
Male	75.72%	72.63%	76.98%	86.17%
Female	24.16%	27.22%	23.01%	13.68%
Missing	0.12%	0.09%	0.01%	0.14%
Race				
Black	29.93%	28.23%	28.65%	37.73%
Hispanic	40.23%	42.22%	38.06%	34.94%
White	21.17%	21.90%	22.40%	17.13%
Other	7.21%	7.38%	7.57%	2.98%
Missing	1.45%	0.26%	0.28%	7.22%
Gang Membership	10.76%	3.25%	13.07%	36.97%

However, if the main purpose of using FI cards is to assist in the prevention of crime by documenting suspicious activity, these findings raise some doubt regarding whether FI cards are efficient tools for that purpose. We could interpret the fact that such a large proportion of individuals FI'd were never arrested during the time period as meaning that officers' suspicions are often unfounded. Conversely, this could be evidence of officers' discretionary leniency towards certain crimes.

Another important purpose of FI cards is to document gang membership and for that particular purpose it appears to a particularly efficient tool judging by the proportion of gang members in the FIs only and Arrests+FIs sample. Nearly 37% of individuals who were arrested *and* FI'd, and a little over 13% of those who were only FI'd in Long Beach during the study period were at some point identified as gang members. Comparatively, only 3.25% of individuals who were only arrested were ever identified as gang members. Clearly, FI cards are used by the LBPD to keep tabs on gang members within their cities and for the most part they appear to be an effective tool in doing so considering that 80.36% of all gang members identified through FI and arrest records over the study period, and 74.89% of gang members arrested between 2008 and 2013 (i.e. arrested at least once) were part of an FI stop.

However, the fact that 13.07% of gang members were never arrested during the time period may suggest that police officer are identifying individuals as gang members that may not actually be involved with gangs. Of course, we should not lose sight of the nature of the present data: it is entirely possible that these members were simply never caught or committed crimes outside of LBPD's jurisdiction. Furthermore, while the positive correlation between gang membership and delinquency is a robust finding in criminology (Pyrooz, Turanovic, Decker, & Wu, 2016), the influence of gang membership on the probability of arrest is not as well demonstrated. For instance, Brownfield, Sorenson, & Thompson (2001) found no evidence of a higher likelihood of arrests for gang members once they controlled for self-reported delinquency. Other studies suggest that the influence of gang membership on the probability of arrest is in large part explained by the fact that gang members are often members of minority racial and ethnic groups (Tapia, 2011).

Conclusions

This chapter described the process of cleaning the data used for the creation of networks extracted from these data. I have made several observations regarding the composition of arrest and FI records that are worth discussing further and that will guide the analyses in subsequent chapters of this dissertation.

First, an important observation from the arrest records is that by far the most important source of ties comes from QOL crimes. The fact that QOL crimes appear to be the more "social" type of crime event is not surprising given that this category includes many crimes that are likely to involve small groups associating in public such as loitering, truancy, trespassing (e.g. being in public spaces after hours), drinking in public and curfew violations. These types of offenses, often characterized as part of what scholars have called "order-maintenance policing" (e.g. Gau & Brunson, 2010; Sousa, 2010), and have been associated with "broken windows policing". As I will show in the next chapter, the number of arrests for QOL crimes varies considerably over the time period studied. I will examine whether these changes coincide with a reduction in the number of police officers in the LBPD and multiple changes in police chiefs. It follows that any biases associated with the enforcement of QOL crimes will be reflected in the composition and structure of co-arrest networks.

Second, drug-related crimes also emerged as an important source of ties in the co-arrest network. As I will describe in the next chapter, important changes in laws related to minor possession of marijuana occurred during the study period that may have affected the enforcement of these offenses. Much like police organizational changes, legal changes may have an influence on the structure of networks extracted from police data. Variability in arrests for minor marijuana possession affords me a window through which I can test to what extent laws could affect the structure of co-arrest networks.

CHAPTER 3. SOURCES OF VARIABILITY IN POLICE RECORDS

In this chapter, I am focusing on variations over time in police records, particularly for the type of records that generate much of the information about relationships between offenders. The goal of this analysis is to examine the stability of the data generating process behind arrest and FI records. Using the City of Long Beach as a case study, I explore how changes in police leadership, budget constraints leading to a reduction of the police force, and legal changes may have influenced the content of arrest and FI records. This chapter is meant as an exploratory analysis of factors more closely related to the behavior of the officers who observe these events rather than the social behavior of actors we wish to study.

The findings of the previous chapter suggest that a large proportion of the relationships between offenders found in police records are not those that emerge from serious crimes but rather come from arrests for minor crimes such as loitering, trespassing, drinking in public, public urination, and curfew violations. These types of offenses are the same types that are the focus of order-maintenance and broken windows policing (Sousa, 2010; Sousa & Kelling, 2010; Wilson & Kelling, 1982). This approach to policing championed by Wilson and Kelling (1982) is based on the premise that if visible disorder in the city goes unpunished, crime—serious crime—will go rampant. The simple but appealing theory rapidly spread through the policing community in the 1990s and remains a very well engrained idea in police departments to this day (Bratton & Kelling, 2015; Harcourt, 2008; Jenkins, 2016; Taylor, 2001; Welsh, Braga & Bruinsma, 2015).

Given the apparent importance minor crimes are in the identification of social relationships in police data, any process that influences their enforcement and/or recording by police officers will in turn have an important influence on the structure of networks we observe.

There are several factors that may influence the intensity of enforcement of minor offenses. Police officers attitudes, and the attitudes of their supervisors have been shown to influence the amount of time officers spend on activities related to community policing (Wilson, 1968; Engel & Worden, 2003), including their decisions to arrests individuals they encounter while patrolling (Mastrofski, Worden, & Snipes, 1995).

The demands of police work require that officers be given considerable discretion in considering when to make an arrest or when to investigate suspicious behavior. The decision to act is highly influenced by the situational characteristics of the encounter that led to the decision (Bittner, 1967; Black, 1970; Mastrofski, 2004) and the demeanor of the suspect (Engel, Sobol, & Worden, 2000; Lundman, 1994; Worden & Shepard, 1996). Most research has focused on the decision making process of officers based on the race, ethnicity, and socio-economic status of those involved in police encounters, particularly in the context of order-maintenance policing. The most common critique associated with the aggressive enforcement of quality-of-life offenses associated with broken windows policing is that it disproportionately affects "poor people in poor places" (Fagan & Davies, 2000, p.496). Furthermore, as Harcourt (2008, p.342) observed, broken windows policing "[has] little to do with fixing broken windows and much more to do with arresting window breakers—or persons who look like they might break windows". Research has repeatedly shown that aggressive enforcement of quality-of-life offenses, and similar initiatives such as "stop and frisk" policies disproportionally affect poor, young men of color (Fagan, Geller, Davies, & West, 2010; Fagan & Davies, 2000; Gau & Brunson, 2010; Gelman, Fagan, & Kiss, 2007). In recent years, many have argued that even if broken windows and order maintenance policing could lead to short-term reduction in crime, it comes at the cost of eroding the public's beliefs about police legitimacy, particularly in communities of color

(Brunson, 2007; Brunson & Weitzer, 2009; Carr, Napolitano, & Keating, 2007; Gau & Brunson, 2010; Kubrin, 2008; Meares, 2015; Tyler, Fagan, & Geller, 2014).

Since the work of Wilson (1968), very little work has considered how variations in the styles of police administration affect the conduct of officers. In fact, Klinger (2004) observed that police scholars have largely ignored the question of how organizational factors affect the behavior of police officers. When research has been conducted, the focus has generally been on comparing police departments based on their size (e.g. Ostrom, Parks, Whitaker, 1978), urban versus rural jurisdictions (e.g. Crank, 1990), and the structure of leadership (e.g Wilson, 1968). Such research does not tell us much about the malleability of police departments over time. For instance, we know very little about the ability of a newly appointed police chief to change the day-to-day operations of a police department.

Legal changes and police adaptations

Police departments constantly have to adapt to changes in laws. In some respects, one of the better studied aspect of policing has to do with the influence of mandatory arrest laws and other policies in cases of domestic violence (Dugan, 2003; Hirschel, Buzawa, Pattavina, & Faggiani, 2007; Mignon & Holmes, 1995; Saunders, 1995; Sherman, 2018; Sherman, Schmidt, Rogan, Gartin, Cohn, Collins, & Bacich, 1991). In the 1970s and 1980s, several states enacted laws aimed at reducing police discretion when investigating suspected domestic violence cases and broadening their arrest powers. In some cases, laws stated that arrests were mandated when officers found probable cause, whereas other laws simply stated that an arrest should be the main course of action (Hirschel et al., 2007). Besides leading to an increase in arrests in domestic violence, many authors have noted that police organizations adapted to the passage of laws aimed at influencing police behavior in ways many did not anticipate (Finn, Blackwell, Stalans,

Studdard, & Dugan, 2004; Hirschel et al., 2007). For instance, mandatory arrest laws led to an

increase in the practice of "dual arrest" where officers arrest both the victim and the offender

when responding to domestic violence calls (e.g. Muftic, Bouffard & Bouffard, 2007). In many

cases, the decision to engage in dual arrests was found to be related to officer's perception of

departmental policies (Finn et al., 2004).

Most legal changes are not as deliberately designed to influence police decision-making.

In some cases, changes in local, state, and federal laws can have a more indirect influence on

police departments' use of their resources. For instance, the decriminalization of certain

behaviors and activities can have an influence on police decisions to enforce laws[4]. For instance,

decriminalization of public drunkenness in many cities in 1960s and 1970s was associated with a

reduction in arrests (e.g. Aaronson, Dienes, & Musheno, 1978). However, Aaronson et al. (1978)

found that one response from the police department in Washington D.C. was to charge

individuals found drunk in public under other statutes such as disorderly conduct. Similarly,

Daggett and Rolde (1979) found that in several suburban towns, decriminalization of public

drunkenness led to an increase in jail detentions for individuals found inebriated. The authors

explain that the reason for the unexpected impact of the change in laws was that "[d]runkenness

per se was never the real reason for the arrest" (p.826), but rather was used by officers to deal

with individuals involved in problematic behavior.

A similar legal change more relevant to the present analysis concerns the

decriminalization and legalization of marijuana possession and use. Oregon was the first state to

decriminalize possession of small amounts of marijuana in 1973 and several other state followed

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[4] Decriminalization is different from legalization in that decriminalized offenses often remain
illegal but violations do not lead to jail sentences and in many cases are dealt with as civil
infractions punishable by fine.

suit, including California in 1976 (Maloff, 1981). Much like the effect of the decriminalization of public drunkenness, several studies found a decrease in the number of arrests in states that decriminalized marijuana (e.g. Kreit, 2016; Natapoff, 2015; Single, 1989; Suggs, 1981). However, the fact that infractions for marijuana possession carry less severe penalties does not mean that police department stopped enforcing existing laws. As Geller and Fagan (2010) observed, arrests for marijuana possession in New York City increased substantially in the mid-1990s following the use of aggressive order-maintenance policing strategies despite the fact that the state decriminalized minor possession in 1977. Like public drunkenness offenses, enforcement of marijuana possession may be used as a pretext to initiate searches and provide law enforcement with a legal justification to stop and question individuals they find suspicious (Geller & Fagan, 2010; Natapoff, 2015).

Motivations for the analyses and research questions

The analyses of this chapter were motivated by three sets observations. First, while constructing the social networks, I observed a sharp decline in the number of relationships that could be extracted from police records. Figure 3.1 shows the distribution of unique relationships observed through arrests, FI stops, and both combined by year.

The number of ties fluctuates rather drastically over the study period. From a high of 16,009 unique ties (Arrest+FI records) in 2009, the number of ties in 2013 fell to 8,470. Most of this decrease is attributable to a decrease of ties from arrest records, though FI ties also decrease substantially: From a high of 4,817 ties in 2008, the number of FI ties declined to 2,805 ties[5].

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[5] I have completely reconstructed the network after noticing this decrease to ensure that no problems occurred during the procedure.
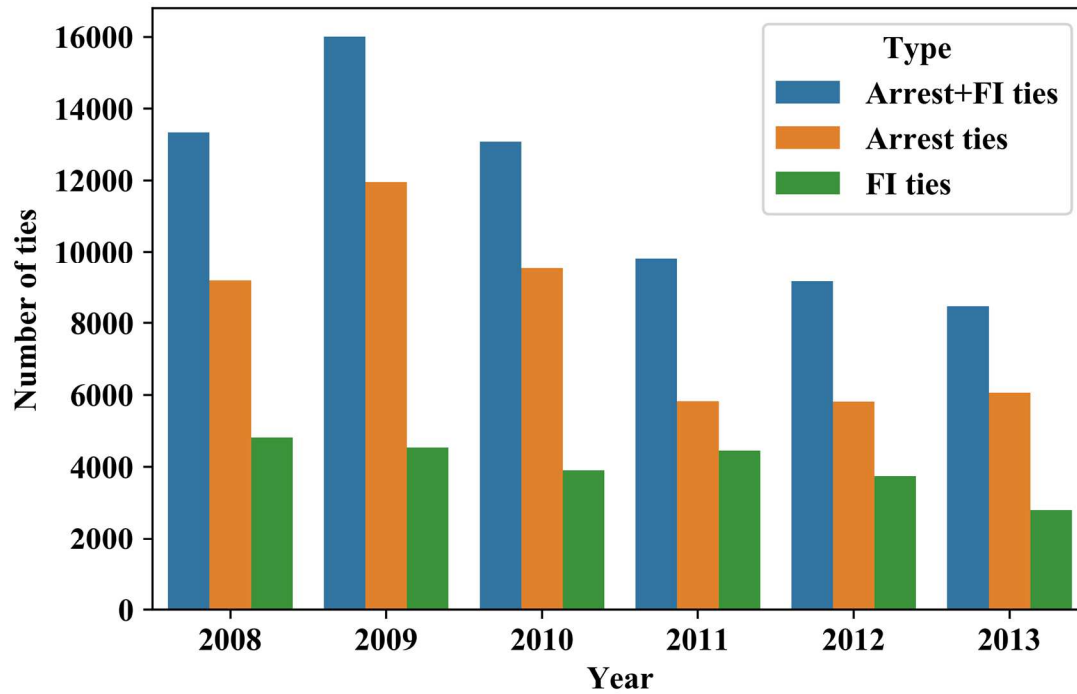
Figure 3.1. Number of ties from arrest and FI records by year

Second, several important changes occurred during the study period both at the local and state level that may have systematically impacted police work. As I describe in more detail below, the LBPD went through several changes in both its leadership and the size of its police force. Furthermore, at least two important social and legal changes occurred during the study period that may have influenced how the LBPD enforcement priorities: changes in attitudes and laws regarding minor possession of marijuana, and a major initiative to reduce the population of State prison known as "realignment".

Third, the focus on these particular changes arose from the fact that the vast majority of relationships in the police data come from what Wilson (1968) called "police-invoked" crimes, and other offenses directly observed by the police such as drug-related crimes. Any systematic change in the ways police officers deal with these types of incidents will have an appreciable

influence on the structure of networks that uses relational data that is extracted from the records of these incidents.

Much of the scholarship, especially more recent work on policing, has focused on situational and individual-level characteristics that affect the likelihood of arrest or investigatory stops. Of course, these well-known biases of the police related to race, ethnicity and socio-economic status will undoubtedly be reflected in the composition of the networks we extract from these records. To the extent that the composition of police records is influenced by the circumstances of a police-citizen encounter, or through relatively stable biases, it may be appropriate to view these as random variations in data-generating process. These are inescapable limitations of police records, regardless of the use researchers make of them. What this chapter is about are those sources of variation that can change the detection of relationships for all officers such that the probability of observing any given relationship at one point in time is not the same at a different point in time. As I have noted above, there appears to be a sharp reduction in the number of relationships observed through police records.

The goal of this chapter is to explore the potential cause for the decline in relationships extracted from police records. The main research question of this chapter is whether changes in the LBPD as well as important changes in local and state policy can explain variations in the composition of arrest and FI data over the study period. In the following sections, I begin by examining the arrest and FI records more in detail to identify sources of variations that may be responsible to the decrease in observed ties. Second, I examine trends in reported crime in Long Beach. Third, I describe several changes in the LBPD that occurred during the study period. Fourth, I consider how two important changes in policy that occurred in California—changes in

marijuana laws and California's Public Safety Realignment—may have impacted policing in Long Beach.

Variations in police records over time

Arrest events

Arrest events are not evenly distributed over time, as shown in Figure 3.2. There appears to be a constant decrease in the number of arrest incidents after 2009. As Figure 3.2 shows, this decrease is also reflected in the number of individuals arrested between 2008 and 2013. From a high of 24,269 individuals arrested in 2009, the number of individuals arrested in 2013 is almost 8,000 less (16,532).
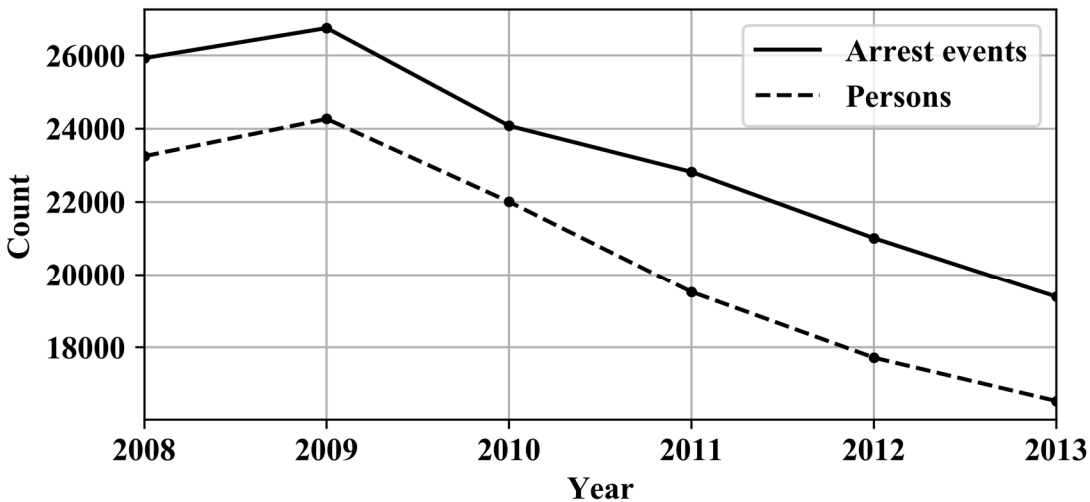
Figure 3.2. Arrest events and persons arrested by year

When we break down the events by crime type, it becomes obvious that most of the decline in arrest events is driven by a handful of crime categories. Figure 3.3 provides the number of events by crime type and shows that the number of events involving QOL offenses rose by 25.16% between 2008 and 2009, before decreasing by 41.96% between 2009 and 2013. Figure 3.3 also shows that drug related crimes have decreased by 47.03% between 2008 and 2012. Most other crime types show very little variability over time. Clearly these crime types

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deserve further attention given that they account for a large proportion of the decline in arrest events.
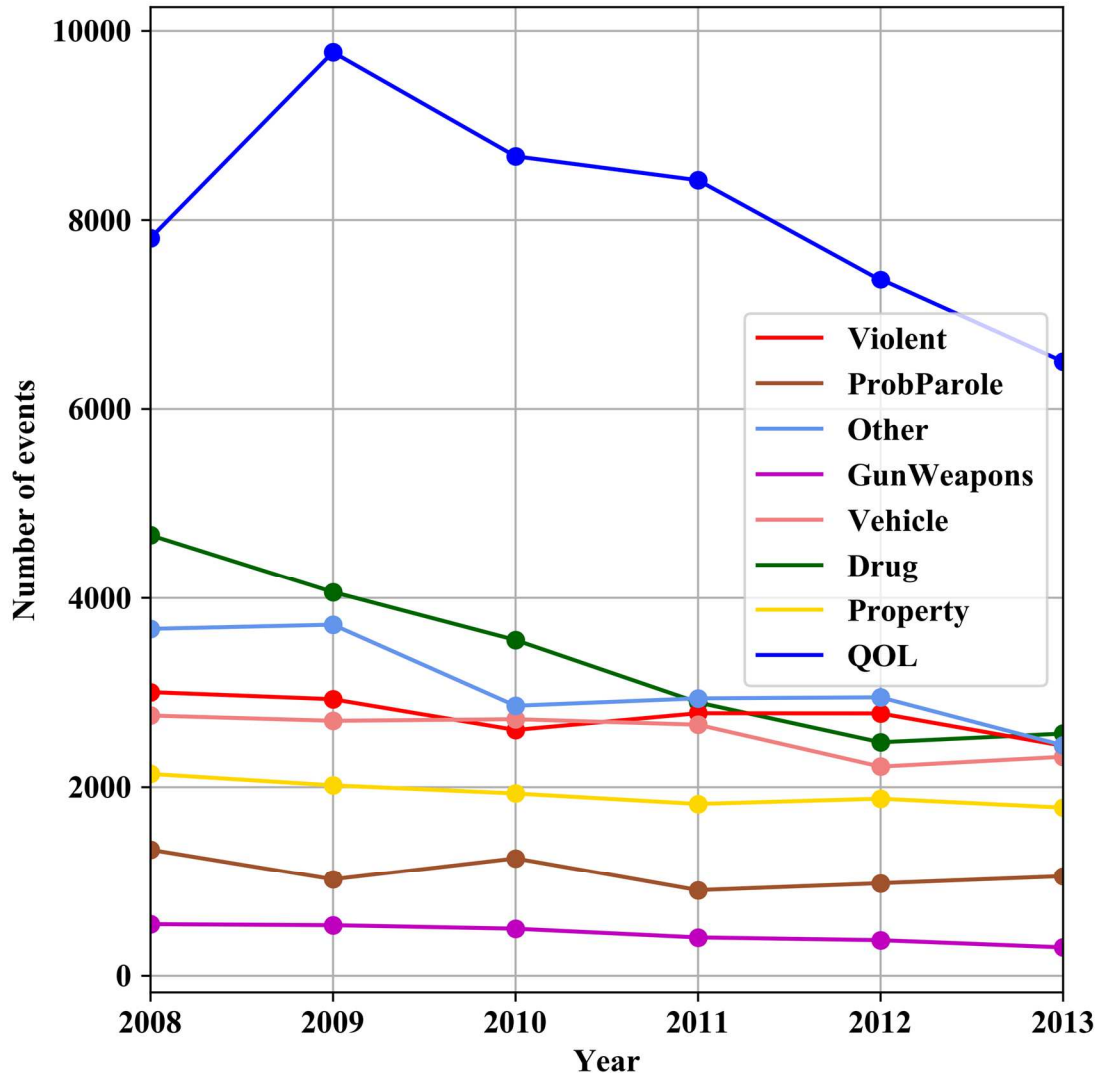
Figure 3.3. Arrest events by crime type and year

FI events

While the number of arrest records showed a downward trend over the time period, the trend in FI events tells a different story. Figure 3.4 shows the number of FI events by year on the left side, and the proportion of FI events that involved groups. The number of FI events increased by 10.50% between 2008 and 2009 and decreased by 2.67% in 2010. The largest change

occurred between 2010 and 2011 where FI events increased by 27.76%, remained high in 2012, before decreasing back to approximately the same number of events as 2009.
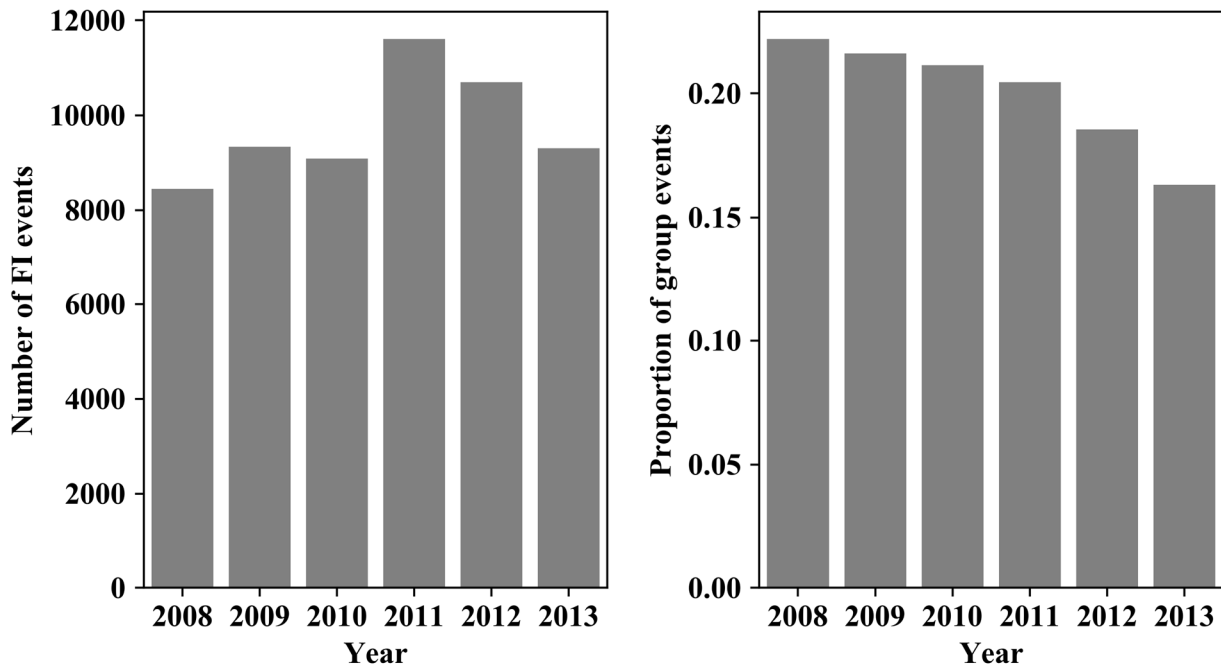
Figure 3.4. Number of FI events (left) and proportion of group FI (right) by year

The right side of Figure 3.4 shows the percentage of these events that involved 2 or more individuals. From a high of 22.19% group events in 2008, the proportion of group events continually decreased over the study period to reach its lowest level in 2013 at 16.32%. Together these figures show that the composition of FI events appears to change around 2011, with a greater emphasis on solo events. When we break down the events by group and gang membership status (Figure 3.5), we can see that most of the increase in FI events is attributable to solo events involving non-gang members. More importantly, Figure 3.5 suggests that an important shift in the composition of FI events after 2010. Whereas gang events—both group and solo events—make up the majority of FI events in the first three years of the study period, non-gang solo events make up the majority of events after 2011.

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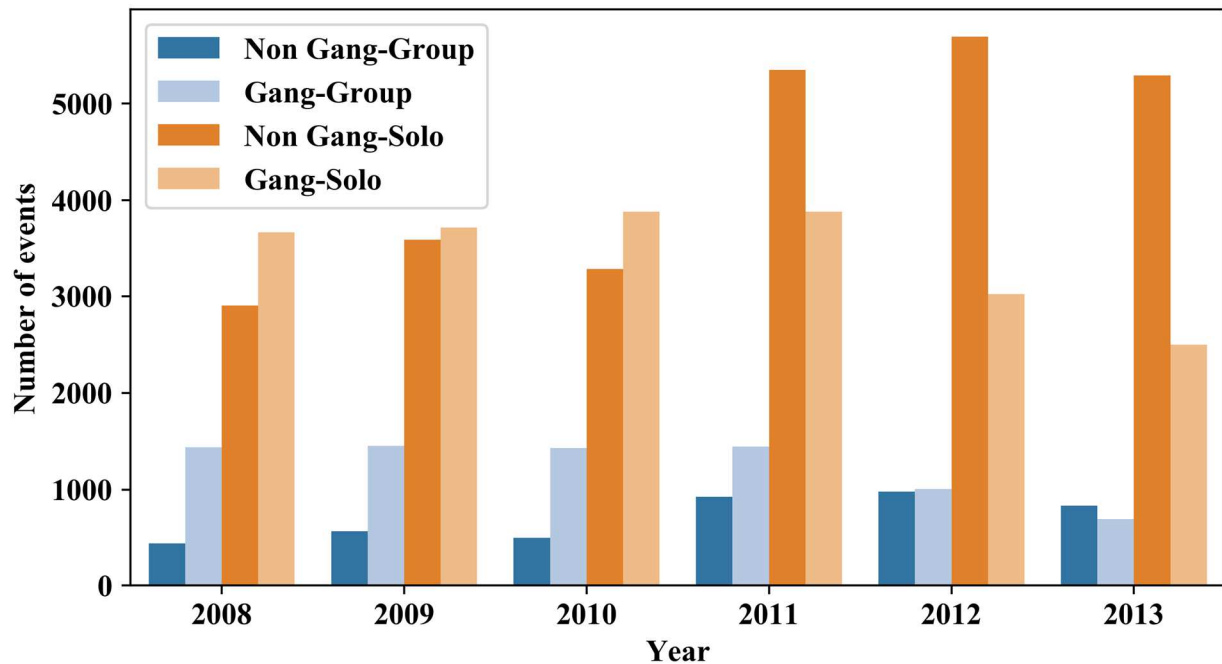
Figure 3.5. Number of FI events by group and gang membership

Hypotheses related to the variation in police records over time

Before exploring plausible hypotheses for the variations I described above, it should be

noted that there is little to suggest that trends in reported crime may be held responsible for the

decrease in arrests. Figure 3.6 shows the trends in UCR violent and property crime rates in Long

Beach from 2000 to 2014. Figure 3.6 shows that while violent crime has been steadily going

down since the early 2000s, property crime rates reported to the police are much more volatile

from one year to the next, particularly between 2010 and 2013. As we have seen in the previous

section, we do not see much variation over time in either violent or property over the study

period. In fact, for most crime types except for Quality-of-Life (QOL) and drug-related crimes

the distribution of arrests is rather stable throughout the study period.

In the following sections, I explore a set of plausible hypotheses that may explain the

variations in police records I have described above. These hypotheses are based on the review of

the literature on policing research and the identification of several important changes that occurred during the study period. First, I examine the hypothesis that a change in leadership combined with a reduction in the police force led to a reduction in the enforcement of QOL offenses. Second, I hypothesize that the further decriminalization of minor marijuana possession in 2010 was responsible for a reduction in arrests for this specific crime. Third, I hypothesize that the implementation of California's Public Safety Realignment influenced the ways LBPD officers used FI stops.
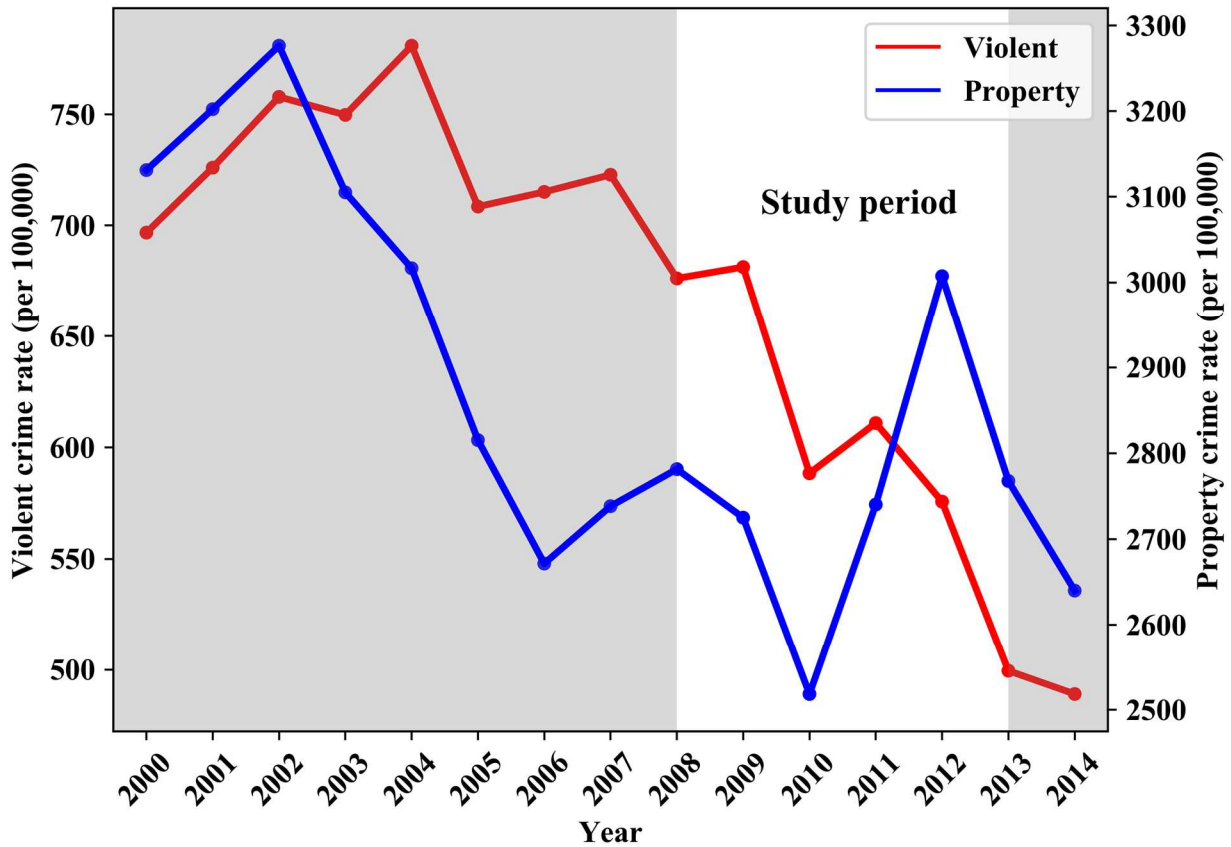
Figure 3.6. Violent and property crime rates for Long Beach (2000-2014)

Police organizational changes

Over the study period (2008-2013), there were many changes in the Long Beach Police Department (LBPD) that may have had an influence on enforcement priorities and, ultimately,

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on the data generated by the work of police officers. After 7 years as the LBPD Chief, Anthony W. Batts resigned in 2009 to become Oakland's Police Chief and eventually Baltimore's and was replaced by interim chief Bill Quach in late 2009. In March 2010, the city appointed Jim McDonnell as Chief—a former Los Angeles Police Department Assistant Chief under Bill Bratton and Charlie Beck. McDonnell would remain LBPD's Chief until he was elected as Los Angeles County Sheriff in November 2014, when he was replaced by long-time LBPD Robert Luna, Long Beach's first Latino Chief of Police.

High turnover and short tenures of police chiefs has been described as the rule rather the exception in past research (Rainguet & Dodge, 2001). Still, changes in organizational leadership are likely to bring about changes in philosophy, priorities, and culture. That said, research on the impact of changes in police chiefs on police organization is practically non-existent. In the mid-2000s, LBPD had integrated a data-driven approach to policing similar to the well-known COMPSTAT system, Bill Bratton's signature "Computerized Statistics" management system that he himself brought to the LAPD in 2003 (Bratton & Malinowski, 2008). Upon joining the LAPD, Bratton actually credited Jim McDonnell for designing the blueprints of what would become LAPD's COMPSTAT system (Blankstein & Barboza, 2010). As an outsider coming into the LBPD, it is possible that McDonnell's background would influence LBPD's operations.

One major innovation, which coincided with McDonnell's appointment[6], was the implementation of two new gang injunctions: the North Side Longos/Surenos and the Insane Crips injunctions. McDonnell (2014, p.5) explained that the LBPD decided to "completely reengineer the city's 18-year-old gang injunction program and take enforcement out of

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[6] Long Beach also elected a new city prosecutor in 2010, Doug Haubert, who ran on the promise of curbing gang violence. The new city prosecutor worked with the LBPD to design Long Beach's Gang Prevention Strategy, of which the expansion of the city's civil gang injunction program was one prong of a multi-prong approach.

detectives' hands and place it instead in the hands of the hundreds of officers patrolling Long Beach streets day and night". Furthermore, McDonnell emphasized the "use of technology to leverage [the injunctions'] impact on the streets" (2014, p.5). Prior to McDonnell's arrival, only officers of the gang unit had access to the gang injunction list and gang officers were responsible for enforcing the injunctions. The LBPD partnered with a technological company to provide a computer system available in all patrol cars to identify gangs and individuals targeted by the injunctions, as well as the specific conditions and geographic areas where they can be enforced.

Beyond changes in leadership, city-level financial difficulties would soon lead to other changes within the LBPD. As Figure 3.7 shows, there was a sizeable decrease in sworn personnel between 2008 and 2013. From 1,020 officers in 2008, the number of sworn officers decreased to 822 in 2013. Despite the changes outlined above regarding gang enforcement, the Gang and Violent crimes division was particularly hit by these cuts in staff. Whereas 45 sworn officers made up the gang unit in 2008, this number would be brought down to 20 in 2012.

It is difficult to disentangle the relationship between size or other organizational characteristics of a police force and reporting practices, and between these factors and crime rates themselves because analyses typically rely on the same data sources. Generally, research finds little evidence that changes in police size leads to changes in crime rates (Weisburd & Eck, 2004). That said, Levitt (1998) using multiple data sources, found that the size of a city's police force may have an influence on crime recording practices. However, the effect is estimated to be rather small: an increase of 1 police officer is associated with 5 more Part 1 crimes being reported (Levitt, 1998).

Logically, a decrease in the size of the police force as the one observed in Long Beach during the study period means less officers to respond to victim complaints and directly observe

crime. Indeed, there was decrease in the number of calls for services the LBPD responded to.

Figure 3.8 shows all calls for service officers responded[7] to (CFS-All) and priority 1, 2, and 3

calls for services[8]. From a high of 738,913 calls in 2008, the number of calls for services reached

its lowest point in 2011 with 607,687. The rather sudden reduction in the number of sworn

officers is likely at least in part responsible for the reduction in the number of calls for services

answered.
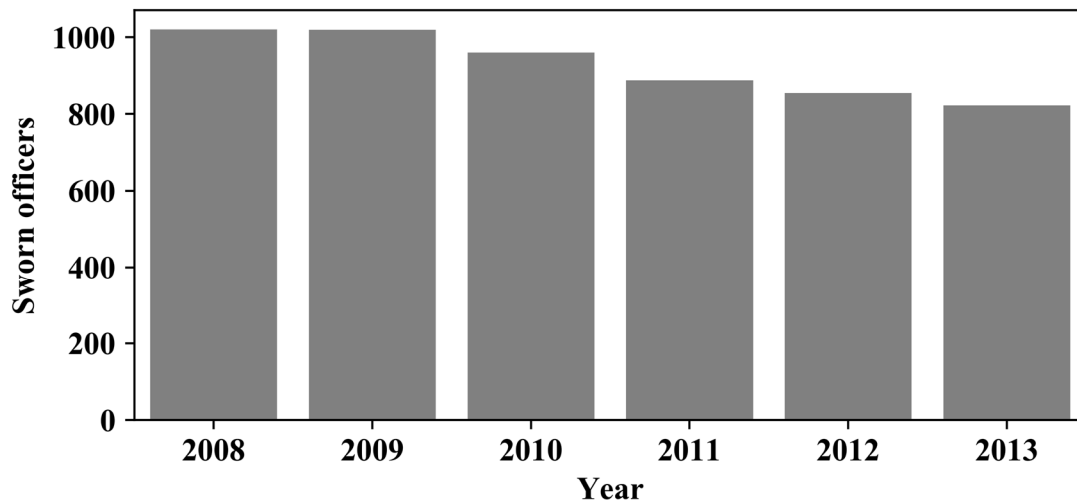
Figure 3.7. Number of sworn officers by year

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[7] The calls for service include all dispatched and officer initiated responses.
[8] Priority 1 calls involved life-threatening situations in progress, priority 2 calls are not life
threatening situations in progress, priority 3 calls are calls for crimes that are not in progress.
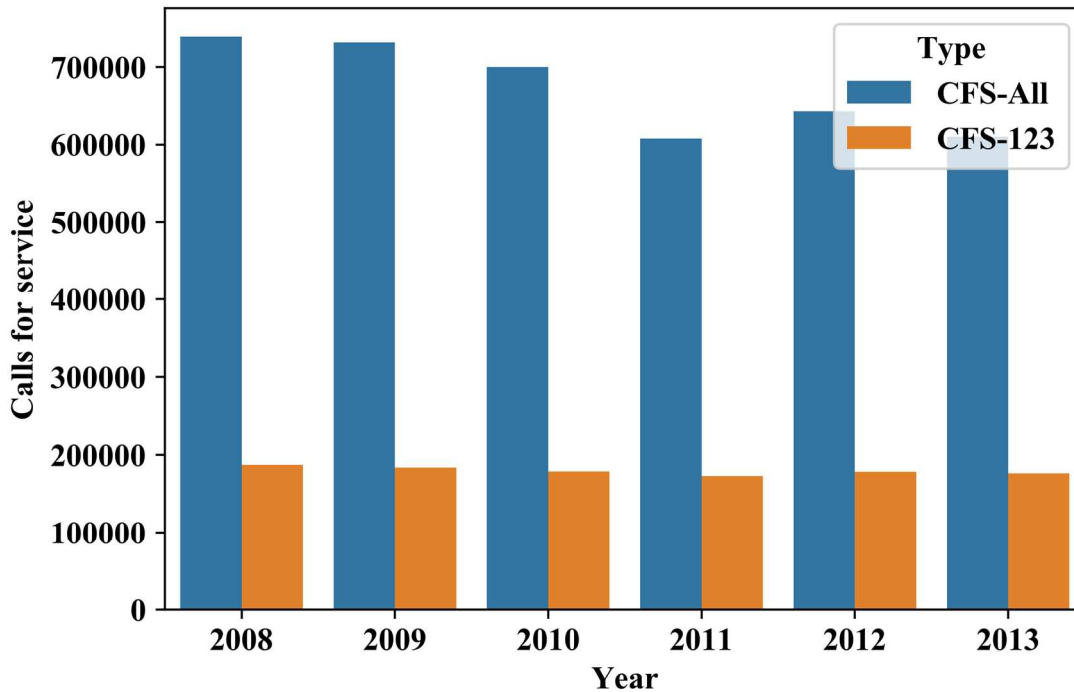
Figure 3.8. Calls for service by year and type

The above observations highlight just how much change occurred in the LBPD during the study period. As we will see below, several state and local legislative changes also occurred during the same time period in addition to these police-level changes. It would be reasonable to expect that such changes would influence the composition of the datasets compiled by police officers. Of particular importance for the present study is whether these changes influence the probability of uncovering relationships between offenders active in Long Beach. There are several mechanisms through which this could occur. First, less officers available may lead to less thorough investigations which may result in the reduction in the number of offenders arrested for a crime that involved multiple offenders. Second, less officers available may result in a reduction of the number of groups recorded in FI data and arrest data, particularly for less serious offenses such as loitering, truancy, and other public nuisances that are directly observed by officers as limited resources may be redirected towards more serious offenses. Similarly, officers faced with

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a greater workload may use more discretion and let more offenders involved in minor offenses off with a warning rather than conduct an arrest or issue citations.

There are also reasons to believe that records of group offenses might increase over the study period. Change in organizational focus towards gang-related crime and the redistribution of the responsibility to serve gang members with injunctions to all patrolling officers may result in officers being more sensitive to groups congregating in public spaces. As patrol officers may not be as knowledgeable about the gang landscape, it is possible that they would cast a much wider net in attempting to enforce gang injunctions than gang unit officers familiar with gang members would. The influence of gang injunctions on police records is the subject of the next chapter.

Changes in the law and attitudes towards minor marijuana possession

I have shown above that drug-related arrests declined between 2008 and 2012 from 4,669 events in 2008 to 2,473 in 2012, though the decrease seems to have halted in 2013. Such a decrease might be explained by changes in laws during this period, particularly as it pertains to marijuana. Figure 3.9 shows that much of the decrease in drug-related arrests in Long Beach is attributable to a decrease in arrests for possession of marijuana.

Two changes are particularly relevant in the present context. First, Senate Bill 1449 reduced the penalty for minor possession (less than one ounce) of marijuana from a misdemeanor to a civil infraction (Ross & Walker, 2017). It is doubtful that this particular legal change directly explains the drop in drug arrests between 2008 and 2012 for at least two reasons: the law went into effect on January 1st 2011, and, even though infractions for minor possession of marijuana are no longer subject to arrests, citations would still be documented in the current database. Second, in 2010, the City of Long Beach attempted to severely impede the establishment of

medical marijuana dispensaries by imposing restrictions on the location and density these establishments. The law was challenged and struck down by the Court, which led the City to subsequently adopt in February 2012 an ordinance completely banning dispensaries. It is possible that this law led to a slight increase in arrests in 2013, or at least contributed to halting the downward trend.
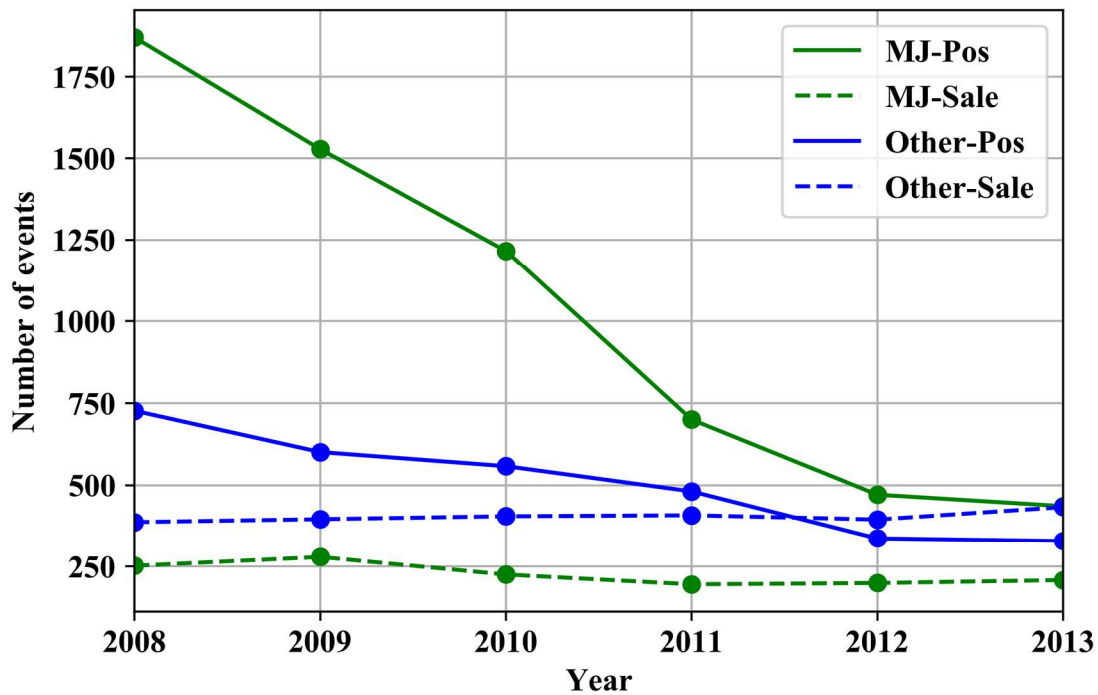
Figure 3.9. Arrest events for marijuana (MJ) and other drug-related offenses

Perhaps a more likely explanation is that the increasing social acceptance of marijuana both in public opinion and through increasingly permissive laws, has led to more selective enforcement of marijuana possession laws. There is evidence from research in the 1970s and 1980s when states like California and Nebraska began decriminalizing minor possession of marijuana, that police officers reduced their enforcement of these laws (e.g. Beck & Summons, 1984; Suggs, 1981). However, more recently Nguyen and Reuter (2012) showed that the national arrest rates for marijuana possession increased drastically during the 1990s before dropping in

the early 2000s. Geller and Fagan (2010) observed that arrests for minor possession of marijuana are intimately related to order-maintenance policing strategies and the use of "stop and frisk". It could be that the decrease observed in Long Beach is in fact a result of the same process that led to a decrease in the number of QOL arrests.

FI stops and the reaction to realignment

California experienced a major shift in policy with the implementation of AB-109 and AB-117—commonly referred to as "Realignment"—in October 2011, which led to the displacements of thousands of state prison inmates towards county jail, probation, and supervision system (Kubrin & Seron, 2016; Petersilia & Snyder, 2013). In the months leading up to and following the implementation of the policy, law enforcement officials across the state voiced their concern that the release of felons would inevitably lead to a spike in crime rates (e.g. Petersilia et al., 2014). Research on the subject suggests that although realignment had little to no effect on violent crime rates, the policy may have been responsible for a modest increase in property crime rates (Petersilia & Snyder, 2013).

Petersilia et al. (2014) interviewed several police chiefs and other law enforcement official about the effect realignment had on street-level policing. The timing of realignment coincided with increasing budget cuts and reductions in the number of officers in police departments across the State. Petersilia et al. (2014, p.68) reported that "[a]lready resource-starved police departments are being forced to divert further resources to conduct compliance checks on the recently released probation population and other offenders on community supervision". Furthermore, police official raised the issue that police departments did not have access to a statewide database of probationers, which made their monitoring effort more difficult. Prior to realignment, records of offenders released from state prison on parole were available to

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all police departments because they were stored in a statewide database. With the shift from state

prison to county jails, many of the offenders are released on probation, which is a county-level

system. As Petersilia et al. (2014) pointed out, these issues are particularly salient for

jurisdictions close to county lines.

For law enforcement official interviewed by Petersilia et al. (2014) the increase in crime

rates is not solely due to recidivism from released offenders, but also because of the redirection

of police efforts away from enforcing low-level crimes and engaging in community and broken

windows policing. While Petersilia et al.'s research is enlightening as to police officials'

perspective on the impact of realignment, there has not been much academic research on how

realignment impacted the day-to-day work of police officers. As we have seen previously, the

City of Long Beach and its police department share many of the characteristics of other cities in

California whose law enforcement officials saw realignment as a substantial burden adding to

existing concerns: a shrinking police force, substantial budget cuts, and potential concerns

related to not being able to access probation records for offenders crossing county lines given its

proximity to Orange County.

Both LBPD Chief Jim McDonnell and Long Beach City Prosecutor Doug Haubert were

very vocal in their opposition to realignment both prior and after its implementation. Chief

McDonnell was quoted in an article published in September 2011 in a local newspaper:

"The scope of the realignment goes far beyond what was envisioned as a cost-cutting measure
[…]When you look at the significant reductions of officers in the community, the dramatic
reductions of parole agents in the state and this very dramatic increase of the inmate population
into the community, it's almost a perfect storm." (Manzer, 2011, p.1A)

City Prosecutor Doug Haubert argued in an opinion piece for the same local newspaper

that the situation in Los Angeles County might be even more dire than in other counties:

"By the way, 'massive early releases' has been the norm in Los Angeles County for years. Violent criminals convicted of misdemeanor crimes often spend less than a week in jail for 60-or 90-day sentences because the sheriff lacks space and resources. If realignment results in massive early releases statewide, the releases will be more 'massive' and 'earlier' here" (Haubert, 2011, p.15A)

Haubert also argued that "[t]here is a perfect storm brewing" because inmates returning were unlikely to find jobs in a county with high unemployment and thus, "many who are released will return to crime. For some, a life of crime is all they know."

The Long Beach Police Department was clearly concerned by the implementation of realignment. In his budget proposal to the City for fiscal year 2012, 2013, and 2014, Chief McDonnell warned that violent crime rates may increase due to the economic downturn, realignment, and reduction in staffing (City of Long Beach-Police, 2011; 2012; 2013). However, in 2014 in his last budget proposal before leaving his post as Chief, McDonnell noted that the violent crime rate "hit a 42-year low" and attributed this decrease to "aggressive efforts in Post Release Community Supervision (PRCS) through the Department's Public Safety Realignment Team", though he warned that "federal changes to expand the definition of sex crimes will result in a greater number of violent crimes recorded in FY15 and beyond" (City of Long Beach-Police, 2014). While fears that realignment would lead to an increase in violent crime did not materialize, it is clear that the LBPD was very apprehensive of the impact it would have on their operations. The "Public Safety Realignment Team" McDonnell referred to in the quote above was a specialized unit created in 2013 dedicated to the monitoring of offenders released from county jails.

Prior to the establishment of a specialized unit, it is possible that LBPD officers used other tools at their disposition to identify newly released offenders. In a previous section of this chapter, I argued that the nature of FI records appeared to change around 2011, with the focus

apparently shifting from a focus on gang members to a focus on non-gang members, particularly for solo FI events. Figure 3.10 breaks down the number of FI events by group and gang membership for each month. Most of the increase in solo non-gang FIs in 2011 occurred in the early months of the year, before any offenders were released under AB-109. However, as we will examine in the next chapter, this increase—which is also reflected in gang events—may be related to the implementation of new gang injunctions. The second notable increase in non-gang solo events occurred in the first few months of 2012. It is difficult to attribute this particular increase in FI events to the LBPD's efforts to deal with offenders released under realignment, though it is a plausible explanation given its timing.

An additional indication that realignment may have influenced the way FI cards are used can be seen from the narratives of the FI cards. Given the number of FI cards, it is impossible to precisely classify which events may have been the result of a probation or parole check on the part of officers. However, officers will frequently note whether an individual is on parole or on probation in the narratives of the events, so it is possible to search for events that mentions the words "parole", "probation" and "PRCS" within the cards narratives. Figure 3.11 describes the number of events with mentions of these three key words by year. While this is a rather crude measure of the purpose of the use of FI cards, the figure does suggest an influence of realignment on the type of supervision encountered by officers in 2012 and 2013. While cards mentioning the word "parole" increase up to 2011, the number of mentions drops in 2012 and 2013, whereas mentions of "probation" remain high, particularly in 2012. Mentions of PRCS begin appearing in 2012, and increase in 2013.
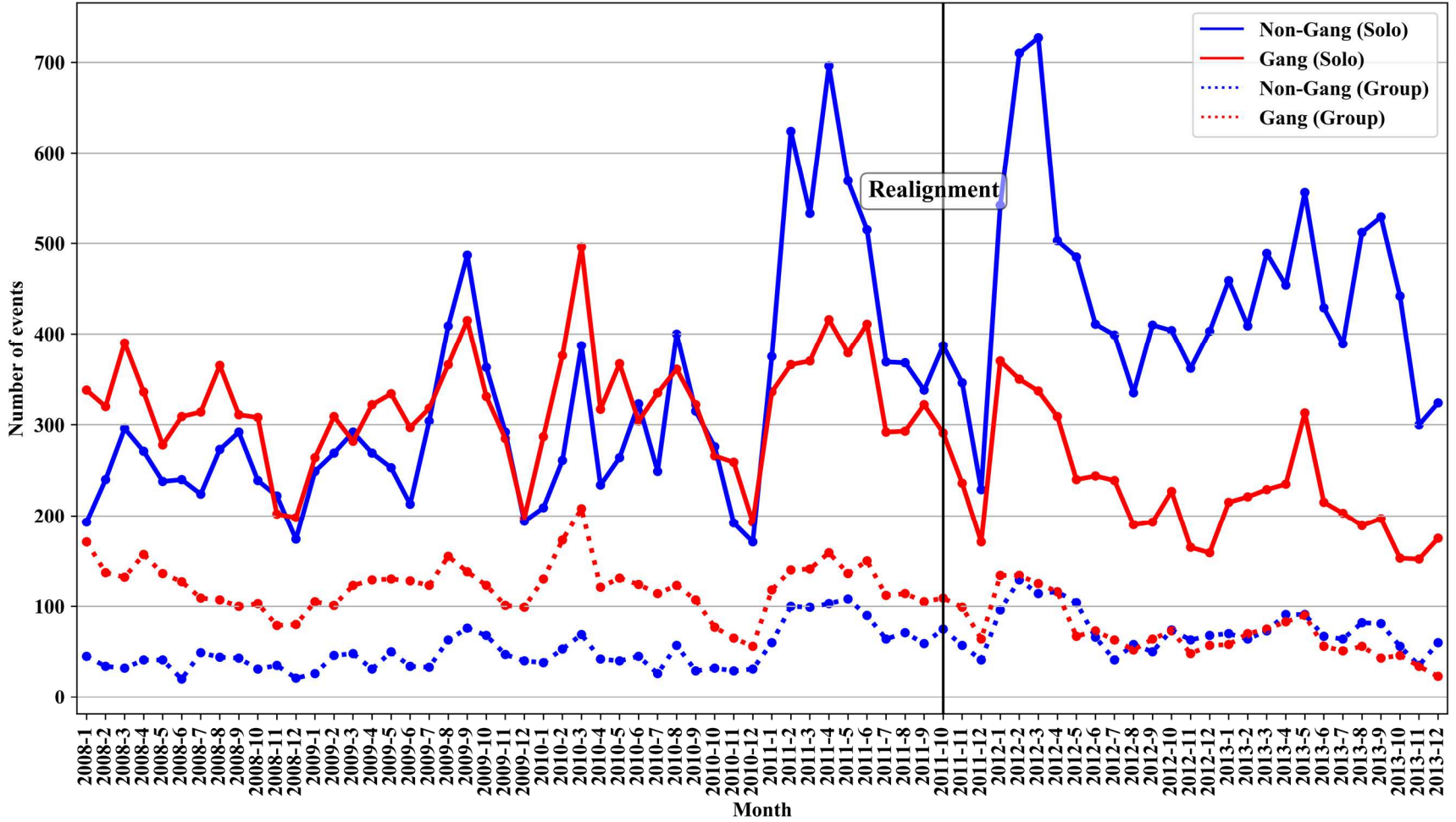
Figure 3.10. FI events by gang membership and group/solo type by month
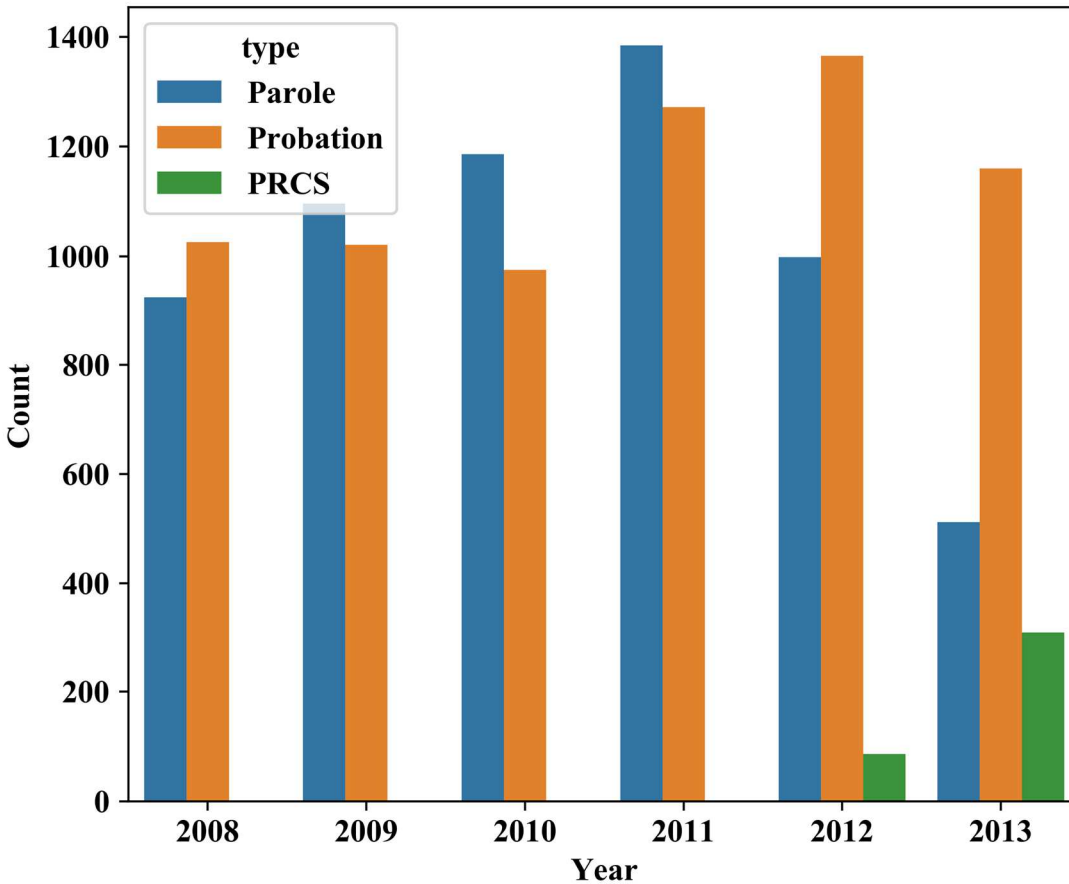
Figure 3.11. Mentions of parole, probation and post-release community supervision (PRCS) in FI narratives

Discussion

The goal of this chapter was to explore potential sources of variations in the ways arrest

and FI records are collected by police officers, particularly those records that generate much of

the information on relationships among people that come into contact with the police. As it turns

out, most relationships in social networks based on co-arrest come from incidents and situations

that are likely to involve substantial police discretion. It is a well-known fact that the

enforcement of minor drug possession and offenses related to order-maintenance such as QOL

offenses are not randomly distributed across space and social groups (e.g. Geller & Fagan, 2010;

Stuart, 2016). This is certainly the case in this data. For instance, I have highlighted in the previous chapter that it is certainly the case that both arrest and FIs generally involve disproportionally more African Americans than would be expected given the racial and ethnic composition of the city. That said, this is a one of the well-known limitations of police data and to the extent that police continue to disproportionally encounter or target poor communities of color, we are forced to treat this fact as an unfortunate, but stable fact of police data.

What I attempted to demonstrate in this chapter is that there are many external forces that are likely to influence day-to-day policing. City and municipal police departments are part of an intricate system of institutions, and police administrators must find ways to respond to the needs of the communities they serve while constantly having to adapt to the demands and constraints of the city government that hire and oversee them, and of an ever-evolving criminal justice system. Changes in leadership, budget cuts, decriminalization of certain behaviors, and major policy changes in other branches of the criminal justice system all require police departments to adapt and often try to do more with less resources. The fact of the matter is that there is only so much a police department can do when they have fewer available officers and resources. Police departments must continue to respond to calls for service and investigate serious crimes. As I have shown in this chapter, the reduction in officers did not appear to have an impact on the number of calls for services for priority 1, 2, and 3 the LBPD responded to. However, when we consider all calls for service—which includes officer-initiated responses—we see a reduction that coincides with the reduction in the number of sworn officers. In other words, when police departments are faced with a reduction in resources, the easiest way to cope may to cut back in enforcing and investigating those crimes and infractions they have the most control over—QOL offenses.

For similar reasons, police departments are somewhat limited in the ways they can respond to major policy changes they feel go against their public safety mission. Despite the apprehension with which the LBPD saw California's public safety realignment, there was little they could do about it other than use the tools they had at their disposition. I argued that one way the LBPD could keep tabs on individuals released as a result of realignment was to shift their use of FI cards in order to conduct informal checks on individuals released in the community. While I identified some evidence from the content of FI cards, it is difficult to know for sure whether the shift from the documentation of gang members and groups to the documentation of non-gang single individuals during FI stops was caused by realignment. As I explore in the next chapter, the implementation of several gang injunctions around the same time may have changed the ways FI cards are used, but also how the willingness of those involved in FI stops to admit their gang memberships with officers.

The analyses of this chapter are limited by the fact that several changes occurred in a short period of time, which makes it difficult to truly assess which change is to blame from the rather dramatic changes in certain kinds of police records. It is most likely that the decrease in arrests in minor offenses and in changes in the use of FI cards cannot be attributed to one cause in particular, but a combination of the factors I identified in this chapter. Moreover, we cannot discard the possibility that the changes in QOL and drug-related arrests, and the composition of FI cards are in fact the result of changes in the behavior of individuals typically involved in such police-citizen encounters.

Nevertheless, this chapter presents some compelling evidence that whatever the exact cause for the changes observed, police enforcement of minor crimes that generates most of the relationships that make up co-arrest networks are highly susceptible to external pressures on

police departments. The implication of this finding is that network scholars using such data should be at the very least cognizant of the impact of the local context and broader legal landscape on the production of group events from which relational data is extracted. Although longitudinal analysis of co-arrest networks is very rare (see Charette & Papachristos, 2017; Ouellet, Bouchard & Charette, 2018), some authors have argued that the study of criminal networks should investigate their evolution over time (e.g. Bright, Koskinen, & Malm, 2018; Bouchard & Malm, 2016). While I do agree that longitudinal network analysis could benefit criminological research, I would caution against the use of police data for this purpose given the highly variable nature of the data generating process.

The variable nature of records that generate much of the connectivity in the co-arrest and co-FI networks also has implications for research that combines several years of police data, as is the case for almost all such studies (e.g. Charette & Papachristos, 2017; Gravel, 2013; Papachristos et al., 2015; Papachristos & Wildeman, 2014; Morselli, 2009; Tremblay et al., 2016). If the probability of observing a relationship varies over time to such an extent as it does in the present study, it may be that differences in positional measures such as degree and betweenness centrality between two nodes have much more to do with the difference in police work at the times where they were stopped than their actual pattern of associations. Police officers do not care about how systematically they collect data on social relationships and the results of this chapter suggests that in fact they have many reasons and incentives to modify their use of the tools they have at their disposition to adapt to legal changes.

Finally, while some of the issues I explored in this chapter are quite specific to Long Beach and to California, I do not believe that the variability in records from which relational data is extracted is unique to the LBPD. While policies like realignment are quite unique to the

present context and time period, changes in leadership, fluctuations in personnel, and decriminalization (or legalization) of some offenses such as marijuana possession are issues that are likely to affect most police departments across the country. Before using police data to construct social networks, scholars should pay attention to variations in the production of records from which social ties are inferred, a task that, if it is undertaken, is never documented in research using co-arrest and co-FI networks.

CHAPTER 4. THE INFLUENCE OF CIVIL GANG INJUNCTIONS ON POLICE RECORDS OF GROUP EVENTS

Introduction

In the preceding chapter, I have examined how changes in the LBPD and changes in policies can effect the collection of FI cards and the decision-making process leading to arrest records. Another policy that can have a significant impact on the production of FI cards, and potentially the observation of group events in arrest and FI records is the implementation of civil gang injunctions (CGIs). CGIs are laws specifically designed, among other things, to disrupt the public gathering of gang members within a predefined geographic area (Grogger, 2002; Maxson, Hennigan, & Sloane, 2005; Valasik, 2014).

While CGIs had been implemented in the City of Long Beach before the start of the study period, three new gang injunctions were implemented between 2010 and 2011. As I explain below, these injunctions were quite different than those originally implemented in the late 1990s and early 2000s in that the more recent CGIs were much larger in scope, both in terms of the size of the "safety zones"—geographic areas where the conditions of the injunction can be enforced—and the number of gangs they targeted.

CGIs can have profound impacts on the collection of FI data (and thus the social networks) for two reasons. First, because CGIs typically seek to target public associations between gang members (e.g. Valasik, 2014), an effective CGI will result in gang members adjusting their behaviors. That is, to avoid the consequences of violating the injunction, groups of members may avoid congregating in public spaces. Clearly, this would lead to a reduction in the opportunity for police to come into contact with gang members and thus the number of observed relationships through police stops would be reduced.

Second, the implementation of an injunction by definition gives officers additional reasons to stop suspected gang members. For example, in order for an injunction to be granted by a judge, the City and the police department must provide evidence of the public activities of the gang, as well as a list of specific individuals to be targeted by the injunction. These requirements could presumably lead to an increase in stops involving gang members in the months preceding the implementation. Moreover, once the injunction is granted, gang members must be served with the conditions of the injunction before they can be found to be violating them. These are all reasons that could lead us to expect a increase in the number of stops involving gang members, particularly stops that involve groups of members.

In the following section, I give a brief overview of the literature on the history of CGIs. I will then describe the logic and "theory of change" behind CGIs and will review the evaluation literature on CGIs. I then explain the specific context of the CGIs implemented in Long Beach and outline the different challenges associated with the evaluation of the influence of CGIs on patterns of association. I will present the methodology used for this analysis, followed by the results and the discussion of the implications of these results for CGIs and social network analysis of police data.

Civil gang injunctions (CGIs)

Civil gang injunctions (CGIs) are court orders typically sought by a city or other government entity that name a street gang and its members as the main defendant. The prototypical CGI prohibits members of the named street gang from engaging in several behaviors within the confines of a specified geographic area under threat of criminal sanctions. While many prohibited activities covered by CGIs are already defined as illegal acts (e.g. drug use and possession, possession of a firearm, trespassing, drinking in public, truancy, curfew violations,

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vandalism, etc), it also targets activities not otherwise considered criminal. The most common of such activities–and the focus of the current paper–is the ability to congregate with other gang members in public, but CGIs have covered a host of other behaviors such as signaling at cars, being seen in public with someone in possession of alcohol, wearing gang colors, using gang signals, and many more (Allan, 2004; Caldwell, 2009; Grogger, 2002; Hennigan & Sloane, 2013; Maxson, et al., 2005; Muniz, 2014; O'Deane, 2012). In California, those who violate the conditions of an injunctions may be charged with a willful disobedience of a court order or be found in contempt of the court, which is a misdemeanor offense that is punishable with up to a year in jail and/or up to a $1,000 fine (Cal Pen. Code 166(a)(9), Cal Pen. Code 166(c)(1)).

CGIs are an increasingly popular strategy to address gang-related crime and violence– particularly in Southern California where they were first used (Muniz, 2014; O'Deane, 2012). District Attorneys in Los Angeles County and Orange County began using civil abatements in 1980 to indirectly target gang activities by suing owners of specific properties known to be gang hang- outs for facilitating the criminal activities of the gang (O'Deane, 2012). Soon after, city attorneys began filing temporary restraining orders that named gangs as unincorporated associations (Allan, 2004; O'Deane, 2012). This strategy took advantage of California Corporations Code's definition of unincorporated associations as "groups of two or more persons joined by mutual consent for a common purpose, whether organized for profit or not"(O'Deane, 2012, p.319). Defining gangs as unincorporated associations meant that in order to sue the gang, plaintiffs only needed to notify and serve a few members of the gang considered to be representatives of the group, in order for the lawsuit to move forward and eventually for an injunction to be granted (O'Deane, 2012). Although a handful of CGIs had been filed between 1980 and 1982 (see Maxson, 2004) it is generally reported that the first example of modern CGIs

was the Playboy Gangster Crips (PGC) injunction filed by the City of Los Angeles in 1987 (Muniz, 2014). Three aspects of the PGC injunction are of particular interest for the current study. First, it marked the first time a city sought to include a condition prohibiting public associations of gang members. Second, it set a precedent for subsequent injunctions by naming DOEs–placeholders for the future of inclusion of other members yet to be identified. Third, the injunction was initially intended to cover the entirety of the City of Los Angeles. Ultimately, the judge overseeing the case refused to include restrictions on associations and other legal activities, and limited the injunction zone to a "26-square-block area"(0.065 square miles, or less than 0.02% of the city; O'Deane, 2012, p.320). Still, CGIs filed in years following the PGC injunction were able to include restrictions on associations, particularly after the Supreme Court of California in *People ex. Rel. Gallo v. Acuna* (1997) argued that such restrictions did not violate the First Amendment, as "[f]reedom of association in the sense protected by the First Amendment, 'does not extend to joining with others for the purpose of depriving third parties of their lawful rights.'".

The criminalization of legal behaviors and the inherent difficulties related to the definition of gangs and gang membership have been the source of vehement criticism of CGIs as racist and violations of constitutional rights (e.g. American Civil Liberties Union [ACLU],1997; Caldwell, 2009; Muniz, 2014; Myers, 2009; Smith, 2000; Stewart, 1998). Yet, courts have often chosen to uphold CGIs, which has undoubtedly led to the expansion of their use in California. As of 2011, O'Deane (2012) reported that 150 CGIs had been filed in California, with more than half of CGIs being filed in Los Angeles County. As of February 2018, 46 permanent injunctions are active in the City of Los Angeles alone, enjoining 79 street gangs (Los Angeles City Attorney, n.d.). CGIs are also increasingly being used in other States such as in Texas, Arizona,

Illinois, Wisconsin, Pennsylvania, Georgia, Massachusetts, Utah, Minnesota (Maxson, 2004; O'Deane, 2012), and recently in the United Kingdom (Carr, Slothower, & Parkinson, 2017; Smithson & Ralphs, 2016). The rapid expansion of the use of CGIs has not been paralleled by scientifically sound evaluations of their effectiveness, as is unfortunately typical of most criminal justice policies and programs. Before reviewing the evaluation literature, I begin by describing theory behind how gang injunctions should work.

The theory of change of gang injunctions

In an ideal world, gang programs would be designed and implemented following principles extracted from well-established theories. Unfortunately, this is rarely the case as policies are often implemented based on conventional wisdoms about the nature of problem what should be done about street gangs (Curry, 2010; Klein & Maxson, 2006). In many cases, the theory behind a policy or a program is outlined post hoc by researchers attempting to evaluate its effectiveness (Gravel, Bouchard, Descormiers, Wong, & Morselli, 2013). This is the case for the theory of change behind CGIs.

A theory of change describes the causal link between a program or policy's activities or outputs and the intended outcome of a given program (Weiss, 1995). In the case of CGIs, police departments often state that the ultimate goal of the program is to increase community safety and reduce fear of crime. Long Beach City Prosecutor Doug Haubert described the need for an injunction in the city at a press conference in 2010:

"Members of these gangs want to terrorize the neighborhoods and commercial districts where they operate. They congregate outside schools and in parks, alleyways and storefronts, trying to claim these areas as gang territories. [. . .] North Long Beach belongs to the hard working men and women who call it home. It belongs to the business owners whose investments are helping to revitalize North Long Beach. It does not belong to gang members, and by our action today, we are doing everything in our power to make sure it never does."

While the ultimate goal may be to increase feelings of safety and reduce fear of crime in the community, none of the activities associated with a CGI are directly aimed at changing the feelings of community residents. Rather CGIs hope to reach this general outcome through the accomplishment of several intermediate outcomes thought to be the source of community fear of crime. Although not explicitly stated, an assumption behind CGIs is that a reduction in violence and a reduction in the visibility of gang members will translate into a better environment for the community, an assumption that has been supported to some degree by prior research (e.g. Maxson, et al., 2005).

Gang program evaluations generally study how the implementation of a program affects outcomes such as gang joining and gang-related crimes. However, such an approach to program evaluation misses a critical opportunity to test the theoretical underpinnings of a given intervention. If the enrichment of our theoretical understanding of gangs is not enough of a compelling argument, the well-documented history of unintended consequences of commonsensical, good-intentioned gang programs (e.g. Klein, 1971; Klein & Maxson, 2006) should at least motivate researchers to examine whether programs they are evaluating are influencing behaviors in the ways policy makers and theorists (when they are consulted) assume.

The logical causal chain of events between an intervention's input and the outcomes we wish to ultimately influence should be examined in its entirety, not simply at its beginning and end. Gravel et al. (2013) argued that evaluations of gang programs should examine the more proximate outputs of a program before exploring its effect on more distant outcomes. In doing so, researchers could potentially reinforce their causal claims of effectiveness particularly when true experiments or even rigorous quasi-experimental evaluation designs are not possible.

Furthermore, examining the impact of a program on outcomes that are likely to be directly influenced may provide more insightful answers beyond whether or not a program "works".

From a theoretical perspective, CGIs can be viewed under the lenses of both deterrence theory and broken windows theory. Deterrence theory posits that effective laws prevent crime by increasing the costs associated with a certain kind of behavior or action and by promising to those who engage in those acts that they will be caught and punished swiftly (Zimring & Hawkins, 1973). CGIs are designed to increase both the severity and certainty of punishment for both criminal and non-criminal offenses. For instance, CGIs often include as part of their conditions offenses that are already considered as criminal offenses (e.g. using firearms, drinking in public, drug use, etc.), and thus, increase the potential costs associated with such behaviors. Furthermore, because CGIs are civil laws, the burden of proof is substantially lower than that required for a conviction through a criminal court, enhancing the certainty of punishment associated with certain behavior. Moreover, the fact that gang members are served with the conditions of the injunction serves as a specific deterrent for the individuals served and those in that individual's social network that become aware that their gang is under strict scrutiny from law enforcement.

Relatedly, the logic of targeting collective behavior of the gang in public spaces is reminiscent of broken windows theory (Wilson & Kelling, 1982), which I have discussed in previous chapters. Part of the rationale behind CGIs is that by enforcing seemingly innocuous behaviors such as loitering and other publically visible behaviors of gang members, these laws reduce visible disorder and allow law-abiding citizens and business owners to take back their neighborhoods from the grips of the gangs, to paraphrase City Prosecutor Doug Haubert cited above.

Another relevant perspective to consider when examining the theory of change behind CGIs is routine activity theory (Cohen & Felson, 1979). Routine activity theory posits that crime emerges when a motivated offender, a suitable target and the absence of capable guardians converge in time and space. CGIs can be thought of as acting upon at least two elements of the theory. First, it targets motivated offenders by attempting to restrict the public behavior of gang members in a specific geographic area. This makes many activities such as drug dealing more difficult to conduct for the members targeted by the injunction. Second, it is thought that CGIs also affect the presence of suitable targets in the areas where they are implemented. By restricting public gathering of gang members in front of businesses and on street corners, CGIs are hypothesized to reduce violence by reducing the probability of violent encounters between the gang members targeted and members from rival gangs.

Regardless of the theoretical perspective we choose to explain the potential mechanism through which CGIs could reduce crime and violence, a common thread between these explanations is that CGIs primarily seek to reduce the public presence of gang members in the areas where they are implemented. While reduction in crime and violence may be the ultimate goal of the injunctions, at least one of the ways this can be achieved is by influencing the group behavior of gang members in public spaces.

Effectiveness of CGIs

One of the first assessments of the effectiveness of CGIs was conducted by the ACLU (1997). The ACLU examined reported crimes trends in police reporting districts under the Blythe Street injunction and for the city as a whole. The authors found that between April 1993–when the injunction was granted– and August 1994, violent crime, aggravated assaults, and robberies increased by 27.1%, 35.4%, and 9.6%, respectively, while citywide violent crime and aggravated

assaults rose by 0.5% and 7.8%, and robberies went down by 8.4 %. However, the analysis conducted by the ACLU amounts to visual descriptions of several time series and does not consider factors such as seasonality and stochastic fluctuations in time series.

The first academic study of CGIs was conducted by Grogger (2002). The author examined the effectiveness of 14 injunctions in Los Angeles, including the first two injunctions to be implemented in Long Beach–the West Side Longos (*City of Long Beach v. West Side Longos*, 1995) and the West Coast Crips (*City of Long Beach v. West Coast Crips*, 1997) injunctions. Grogger (2002) compared violent crime counts prior to and after the CGIs were implemented for targeted areas and neighboring areas matched on their pre-intervention levels of crime. Using a difference-in-difference approach, the author reports that the targeted areas experienced an average reduction of 4.99 quarterly violent crimes, whereas the matched comparison areas experience a decrease of 3.49 quarterly violent crimes. Thus, the author concluded that the CGIs were responsible for a reduction of 1.51 quarterly violent crimes in targeted areas, a difference that is marginally significant. Additional analyses revealed that there was no evidence of crime displacement in adjoining areas. Since Grogger's study, only three other studies have examined the influence of CGIs on crime. O'Deane and Morreale (2011) examined the influence of 25 injunctions in Southern California on Part 1 (i.e. serious violent and property crimes) and Part 2 (i.e. less serious crimes) calls for service. The authors matched the 25 injunction areas to control areas "based on four criteria: 1) both gangs are the same ethnicity; 2) close in proximity; 3) close in square mileage; 4) and close in total number of gang members"(O'Deane & Morreale, 2011, p.18). The authors found that areas under injunctions saw a reduction of 12.4% in Part 1 calls for service, a 17.4% in Part 2 calls for service and a 16.4% in overall calls for service.

Rather than evaluating the effect of CGIs on crime rates and calls for service, Carr et al. (2017) examined how CGIs influenced the criminal involvement of individual gang members and gangs targeted by injunctions in the policing area of Meyerside in the City of Liverpool, UK. The authors reported that compared to three years prior to the injunction, gang members under the injunctions reduced their offending by 70% in the three years post injunction, adjusting for the time spent incarcerated. In the absence of a control group, it is difficult to interpret these findings, particularly given the length of the study period and a lack of information regarding the age of gang members when the injunction was implemented.

Hennigan and Sloane (2013) examined violent gang crimes in two areas in Los Angeles where three CGIs were implemented (two CGIs were implemented in the same area of the city). The authors found that violent gang crime in the two areas where injunctions were implemented decreased by 35% (South area) and 14% (North area) compared to the previous year, whereas violent gang crime in citywide increased by 6%. The downward trend continued for the South area as violent gang crime decreased by 17% in the year after injunctions were implemented, compared to a citywide decrease of 11%, and 24% increase in the North area. Examining the effect of CGIs on crime trends was not the primary goal of the study by Hennigan and Sloane (2013). The authors surveyed youths within the safety zones of each of the three CGIs implemented as well as a control area not subjected to a CGI. Pertaining to CGIs, Hennigan and Sloane (2013) found that gang youths in areas with injunctions did not perceive a higher likelihood of getting caught. The authors reported that there was little evidence to suggest that CGIs had a deterrent effect on gang members, but they pointed out that "injunction approaches that include steps to dilute the focus on the gang as a group in favor of individual concerns may decrease gang crime" (p.32). Hennigan and Sloane (2013) suggested that different aspects related

to the implementation of injunctions such as a smaller safety zone tailored to the activities of individual members, an "orientation toward intervention goals rather than exclusively suppression goals" (p.35), and the availability of gang-specific services and programs may enhance the long-term effectiveness of CGIs. The authors also warned that CGIs may have the unintended consequences of strengthening gang cohesion by creating an "us versus them" mentality, particularly if they are implemented in large safety zones and target groups as a whole rather than specific individuals.

Maxson et al. (2005) took a different approach to study the impact of CGIs by surveying attitudes and perceptions of citizens in communities where they are implemented, as well as in nearby communities where CGIs were not implemented. The authors surveyed community members prior and after the implementation of an injunction in San Bernardino, a city approximately 60 miles east of Los Angeles. Maxson et al. (2005) asked survey respondents about their experiences with gangs in their communities, perceptions of the gang and crime problem, and observations about gang visibility and behaviors in their neighborhoods. The authors found modest reductions in the visibility of gang members, in reported levels of fear pertaining to gangs and their members, as well as intimidating encounters between local residents and gang members in injunction areas compared to control areas. Furthermore, the results suggested some reduction in fear of crime in the injunction area, but found no effect on perceptions of social disorder or crime victimization.

Taken together, these studies shows mixed evidence regarding the effectiveness of CGIs. A conclusion that seems somewhat consistent across studies is that if CGIs have any influence on gang behavior, crime, and community perceptions of safety, these effects are modest and are likely to be as varied as the many contexts in which CGIs are implemented. Given the growing

popularity of CGIs, along with legal concerns that have arisen since they were first implemented, it is surprising that so few studies have been conducted on their effectiveness. In fact, given findings reported by Maxson et al. (2005) and Hennigan and Sloane (2013) it appears that CGIs should not be thought of as "one-size-fits-all" strategies, and their findings raise the specter that poorly designed and implemented injunctions could have negative consequences. For instance, Maxson et al. (2005) showed that when police expanded the territory covered by a CGI, the secondary area saw an increase in gang activity, which could have been the result of displacement. The authors also suggested that the "police over-reached by including this neighborhood with less gang activity and less social disorder in the injunction" (p.597) and that may have increased the gang's cohesiveness or defiance towards the police.

CGIs in Long Beach

As mentioned before, CGIs are not new in Long Beach. The first injunction implemented in the city enjoined the West Side Longos in 1995 (*City of Long Beach v. West Side Longos, 1995)*, followed two years later by an injunction on the West Coast Crips (*City of Long Beach v. West Coast Crips*, *1997*). Other injunctions were implemented in the early 2000s against the East Side Longos (*People v. Eastside Longos, 2001*), the Insane Crips (*People v. Insane Crips, 2003*) and—for the second time—the West Side Longos (*People v. Westside Longos, 2004*).

While the first two injunctions were part of Grogger's 2002 study of gang injunction, we know very little about the effectiveness of these injunctions. In theory, these injunctions are permanent and therefore could still be enforced though in practice they are no longer being enforced (O'Deane, 2012). An investigation by the Long Beach Press Telegram, a local newspaper, found that 80% of the members named in the 2001 ESL injunction and in the 1997 West Coast Crips injunction committed at least one other crime since being named on the

injection (Russell, 2003). The article further noted that aggravated assaults and robberies in the area covered by the ESL injunction increased in the year following its implementation.

Since then, four new injunctions have been implemented in Long Beach between 2010 and 2014. The first injunction targeted the Insane Crips Gang (ICG) was granted in late February 2010, only a few days before the appointment of new Chief Jim McDonnell in March 2010. The injunction covered an area of 10.05 square miles divided in two safety zones shown in Figure 4.1, which covered close to 19% of the entire city. To put the size of this injunction in perspective, according to statistics reported by O'Deane (2012), the average size of CGI safety zones in California was 1.8 square miles. As we will see below, the safety zones for the next two injunctions implemented were even larger and completely included the ICG injunction zones. Court documents show that the injunction includes up to 1250 "DOEs", which are placeholders used in CGIs in addition to members specifically named on the court injunction. This means that in theory, if LBPD can prove that 1250 other individuals are members of ICG, they can be added to the injunction at any time. Perhaps because of its timing coinciding with the changes in police chief and the election of a new City Prosecutor, this particular injunction was not publicized in the media, at least not to the same extent as the other two injunctions I will describe below.
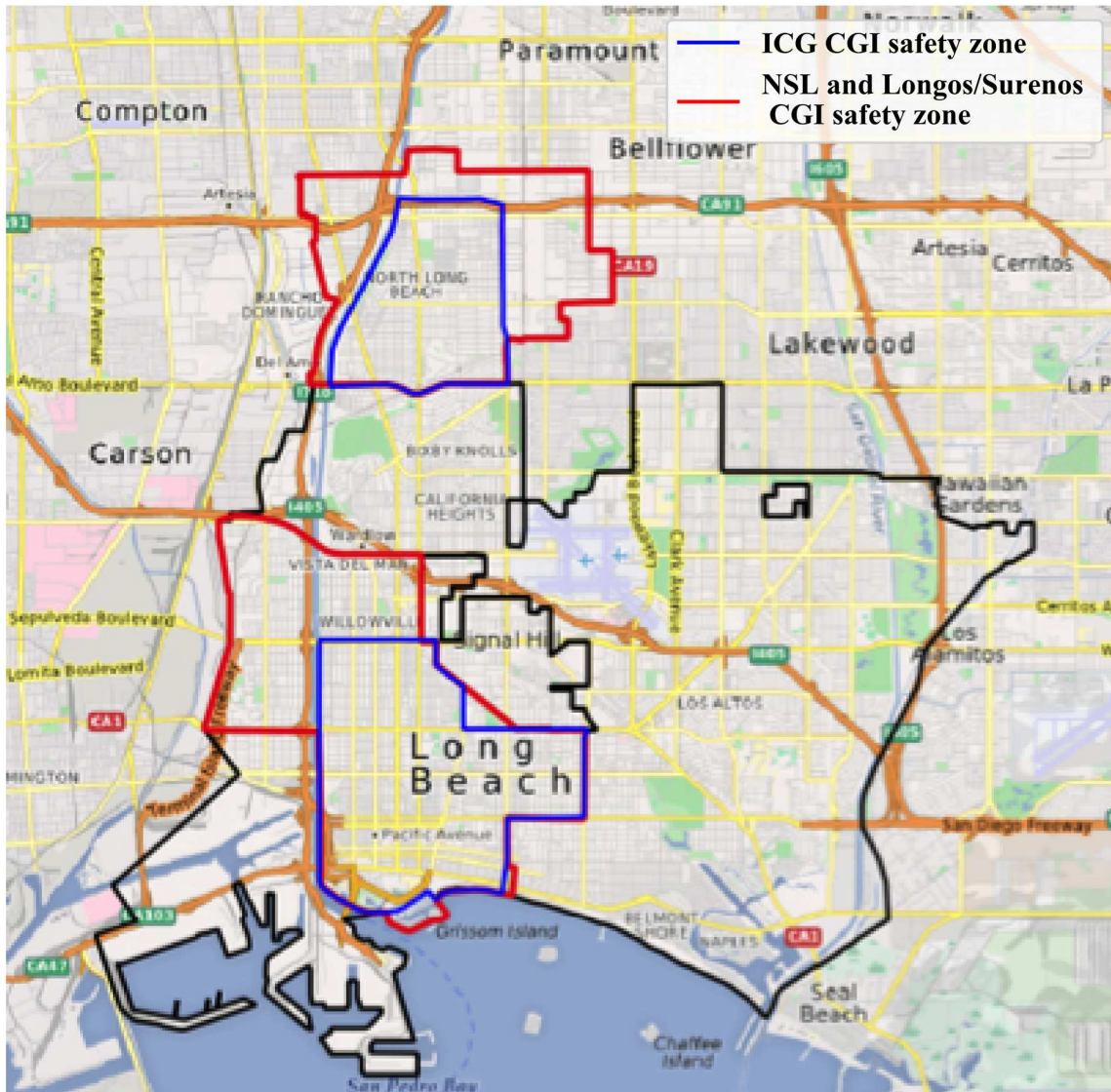
Figure 4.1. Map of CGI safety zones in Long Beach

Later in 2010, the LBPD, in concert with newly-elected City Prosecutor Doug Haubert, "completely reengineer[ed] the city's 18-year-old gang injunction program and [took] enforcement of that program out of detectives' hands and place[d] it instead in the hands of hundreds of officers patrolling Long Beach streets day and night." (McDonnell, 2014, p. 5). This "reengineering" involved the implementation of three new injunctions between 2010 and 2014,

and a program called "Operation Opt-Out" designed to allow gang members to be removed from the city's injunctions provided they decide to leave the gang, stay in school, and perform community service. On the enforcement side, the LBPD made information regarding the conditions and safety zones of the injunctions, as well as the members that were named and had been served with the conditions of the injunction available in every patrol car in Long Beach (McDonnell & Wacker, 2012).

However, what made these injunctions so innovative according to Haubert and Chief McDonnell, is the fact that rather than name a specific gang, the new injunctions targeted an entire organization of gangs named the Surenos, instead of naming the specific gangs under its control. According to McDonnell and Wacker (2012, p. 3), "whether an individual gang member on the streets of Long Beach pledges allegiance to Barrio Pobre, Eastside Longos, Compton Barrio, 18th Street or any other gangs operating in the area, they all are controlled by the Surenos, which takes its orders from the Mexican Mafia from behind the bars of Pelican Bay State Prison."

Two new injunctions were implemented targeting the Surenos. The first was granted in mid-September 2010 and targeted the North Side Longos (NSL) and Surenos active in North Long Beach. The second injunction was approved at the end of May 2011 and targeted the Longos (east and west side) and Surenos in a safety zone that included the southern ICG safety zone and the entirety of Long Beach's downtown core. Together with the NSL injunction, the Longos/Surenos injunction safety zone covered 17.97 square miles or 34% of the city (Figure 4.1).

A fourth injunction targeted all Crips gangs and other groups active in Long Beach—13 specific gangs and all members affiliated to Crips sets, including the Asian Boyz (ABZ), Sons of

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Samoa (SOS), Rollin 20s (RTC), and ICG. However, this injunction was approved in 2015, which is beyond my study period.

Challenges in the evaluation of the effect of Long Beach's CGIs
Searching for a counter factual

A common quasi-experimental approach in evaluating place-based policies and programs is to identify spatial areas that have not been subjected to the treatment, but that are similar to the treated areas, particularly on pre-intervention levels of the dependent variable. This is a rather difficult task to accomplish for this study because of the size of the injunction safety zones. The ICG injunction covers an area of 10.05 square miles, or 18.83% of the entire city. Together, the NSL and Longos/Surenos CGIs include the entirety of both ICG safety zones and further added a combined 7.92 square miles to the area covered by CGIs in Long Beach. In total, after the implementation of the Longos/Surenos CGI in 2011, 17.97 square miles or approximately 34% of the city was included in CGI safety zones. To put that number in perspective, according to statistics reported by O'Deane (2012), the average size of CGI safety zones in California was 1.8 square miles.

Figure 4.2 shows the locations of arrest events in the two years (2008 and 2009) prior the implementation of the ICG injunction. The map clearly shows the problem in identifying comparable areas of the city zones in terms of crime as most arrests fall within the expansive safety zones. Taken together, the CGI safety zones include 81.87% of FI events, and 80.20% of arrest events recorded between 2008 and 2013.

An alternative approach to finding a counter-factual to evaluate the effect of CGIs is to compare changes in arrests and FI stops of targeted gangs to those of gangs not targeted by the CGIs. For the ICG injunction, a potential candidate is the Rollin 20's Crips (RTC). While the number RTC members active and identified by police during the study period is about half (503

members) that of ICG members (1,136 members), RTC is similar in many other respects to ICG: both gangs are primarily African-American gangs claiming allegiance to the Crips, and their territories (according to the LBPD) are adjacent to one another in the southern safety zone. The inclusion of a safety zone for the ICG CGI is curious since ICG members were rarely stopped in North Long Beach. One gang detective explained that at the time the injunction was filed, ICG members had been involved in several shootings in North Long Beach, which was interpreted by the police as an attempt by the gang to expand their territory, and motivated the addition of this second ICG safety zone.

The language of the NSL and Longos/Surenos injunctions make it more difficult to identify "untreated" gangs as comparison groups. The NSL injunction specifically names the North Side Longos (NSL), but also includes gangs that fall under the umbrella of the Surenos, a group of Latino gangs that allegedly act as foot soldiers for the Mexican Mafia, a gang primarily active in prisons in California and across the United States. While most individuals that have been served with the NSL injunction belong to the NSL, members of different cliques of Compton Varrio, East Side Paramount (ESP), 18th Street, Big Hazard, Florencia 13 (F13), Barrio Pobre (BP), White Fence, Westside Wilmas, as well as members of other Longos cliques (ESL, WSL) have also been served with the NSL injunctions. Similarly, the Longos/Surenos CGI implemented a few months after the NSL injunction names all Longos cliques as well as all gangs affiliated with the Surenos, without explicitly naming what these gangs are. When looking at individuals served with the injunction, the vast majority are members of the East Side Longos (ESL), one of the largest gang active in Long Beach. However, much like the NSL CGI, it also includes members of other Latino gangs active in Long Beach. While the official documents

never expressly state it in these terms, the addition of the Surenos to both injunctions effectively

leads to injunctions that target all of the major Latino gangs in Long Beach.
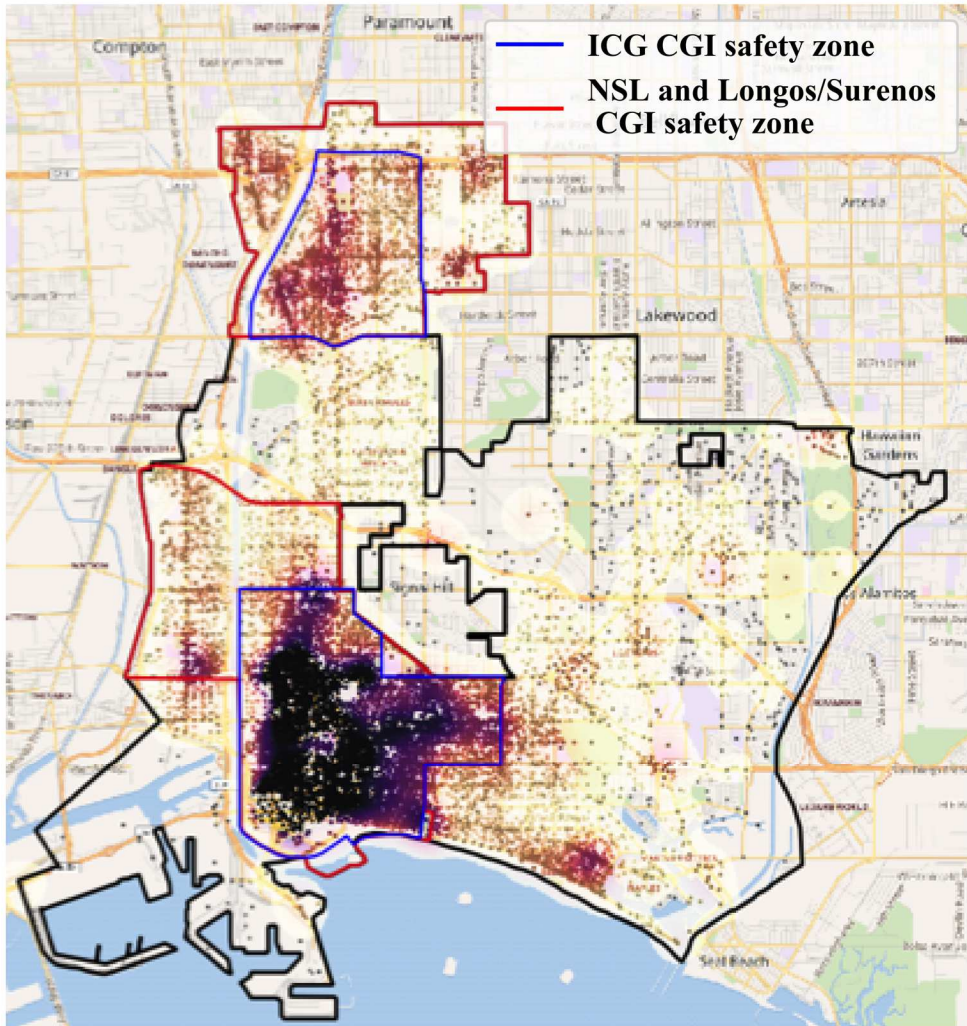
**Figure 4.2. Concentration of arrest events (2008-2009) and
CGI safety zones in Long Beach**

It is easier to identify which gangs are *not* targeted by the NSL and Longos/Surenos

(henceforth referred to collectively as the Surenos injunctions) than it is to identify the ones that

are. None of the Asian and Pacific Islanders gangs were subjected to injunctions between 2008

and 2013, though their turns would come soon after, as the City filed for an injunction

consolidating the ICG injunction by targeting all Crips gangs in December of 2014. The main

Asian and Pacific Islanders gangs active in Long Beach during the study period were the Asian Boyz (ABZ), the Sons of Samoa (SOS), and the Tiny Rascal Gang (TRG). All three gangs were mostly active within the Longos/Surenos safety zone, though they are much smaller than the main gang targeted by the CGI, the ESL. Whereas 862 members of the ESL were identified between 2008 and 2013, 306 ABZ members, 183 SOS members, and 150 TRG members were identified during the same period.

Research question and analytic strategy

The purpose of this chapter is to assess the influence of CGIs on patterns of associations among gang members. As I have explained above, it is assumed that CGIs work by disrupting the public behavior of gang members. Therefore, I hypothesize that group events (FI and Arrests) involving members of gangs targeted will decrease as a result of the implementation of the CGIs. Of course, as I have shown in the previous chapter, it is possible that the implementation of injunctions may influence the ways in which police officers conduct their work, particularly in their use of FI records. Given the available data, it is difficult to distinguish whether changes in records about gang members is in fact a result of behavioral changes on the part of gang members or on the part of the police. In the next sections I focus on two types of police stops: solo and group events. Solo events are FI and arrest events involving a single individual. Group events are FI and arrest events that involve two and more individuals.

We can expect an increase in some type of records—particularly solo events—in the first few months following the implementation of the injunction, as officers attempt to serve members named under the injunction. If the injunction has an influence on group behavior, we should see a long term decrease in group events recorded by police.

The analysis will focus on the southern ICG safety zone, which is included in the Longos/Surenos safety zone. I will focus on three time periods: 1) the pre-ICG period (January 2008 to February 2010), 2) the ICG-Longos period (March 2010 to April 2011), and 3)the post-Longos (May 2011 to December 2013). I first examine changes in the number of events involving the main active gangs within the safety zone. During the ICG-Longos period, only the ICG gang was under injunction, whereas ESL, WSL, BP, and 18th were targeted by an injunction in the post-Longos period. Second, I focus on two sets of time-series in order to examine the effects of the injunctions on the police records of the two main targets of these injunctions. The first set of comparisons will involved the two main African American gangs active within the safety zone, ICG and RTC. The second set of comparisons will focus on the large Latino gangs active within the safety zone (ESL, WSL, BP, 18th) against the main Asian and Pacific Islander gangs, that were not targeted by the injunctions (ABZ, SOS, and TRG). Given my interest in identifying the influence of CGIs on the networks resulting from police data, I will examine trends for solo events and group events separately.

The second set of comparison will use time-series outlier detection techniques based on ARIMA models. I opted to use outlier detection techniques because it is difficult to predict what the shape and timing of the effect injunctions should have on a time series, which makes the proper identification of ARIMA models as one would do using an interrupted time-series design very difficult (McCleary, McDowall, & Bartos, 2017).

Time-series outlier detection

In order to properly model interrupted time-series, researchers must know two things: 1) the exact onset of the intervention, and 2) the hypothesized impact of the intervention (McCleary, et al., 2017). When evaluating the impact of CGIs, it can be difficult to specify a

priori both these components. Thus far, we have used the preliminary injunction date as the start date of the intervention with the rationale that this is the date when officers can begin to serve individuals with the injunction. However, we must not lose sight of the nature of the data used in the current study. Since we are examining the impact of CGIs on FI and Arrest records, one could argue that the process of applying for an injunction may actually lead to an increase in stops involving members or suspected members of the targeted group, meaning that the effect of an injunction on police stops could begin prior to the preliminary injunction date. Furthermore, the legal requirement that members be served with the conditions of the injunction before they can be arrested for violating these conditions may delay the effective start of the treatment until a large enough number of members have been served.

By specifying the "impact" of the intervention, I mean, as did McCleary et al. (2017), that we must rely on theory to posit in what ways we expect the intervention to modify the time series of interest. In order to estimate the impact of an exogenous shock, such as a policy change or a modification in measurement, on a time-series, one must identify the appropriate transfer function that links the time-series for the outcome variable and the time-series of the intervention effect.

In the present study, three types of impacts are plausible. First, an abrupt and permanent shift—also called a level-shift (LS)—indicates a reduction or increase in the level of the time series at a specific time point with the effect remaining for the remainder of the time series. Second, the effect can be abrupt but only last for a single point in the time series, which is referred to as an additive outlier (AO). Third, the effect could be a temporary shift (TS) in the level of the time series with a decaying impact as we move away from the initial change.

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The problem of specifying a transfer-function to model an intervention's impact on a time series can be thought of as mathematically equivalent to the problem of modeling time series with outliers (e.g. Box & Tiao, 1975; Chen & Liu, 1993; Chen & Tiao, 1990; Fox, 1972; Tsay, 1988). In a context where it is difficult to accurately specify a priori the onset and impact of an intervention, and where there is a potential for unspecified changes unrelated to the intervention (e.g. high-profile shooting and other processes), the approach we will take is to treat the identification of the influence of CGIs (if any) on solo and group events as a outlier detection problem.

Chen and Liu (1993) developed a technique that allows for the simultaneous estimation of outlier effects and ARIMA model parameters, which has been implemented in the R package tsoutliers (Lopez-de-Lacalle, 2017). The technique goes through the following iterative procedure:

1.Identify a tentative ARIMA model and compute maximum likelihood estimates of its parameters.

2. Iteratively, for each time point and for each type of outliers (e.g. level-shift (LS), temporary shift (TS) or additive outlier (AO)), the procedure checks the significance of outliers by adding the effect to a regression model and computing the t-statistic of the coefficient.

3. If any outliers are detected, another ARIMA model is estimated without the outliers. The outlier effects are then added to a regression with the new ARIMA model. If the outlier effects are no longer significant, they are dropped from the set of potential outliers.

4. The procedure iterates through steps 1,2, and 3 until each time point and outlier type has been tested.

To facilitate the iterative identification of ARIMA models, the package *tsoutliers* relies on the automated identification of ARIMA model parameters using the auto.arima function of the *forecast* package(version 8.2; Hyndman, O'Hara-Wild, Bergmeir, Razbash, & Wang, 2017). This function attempts to find the best fitting ARIMA model parameters by iteratively changing

the model parameters and accepting a model that exhibits stationarity (using the Augmented Dickey-Fuller (ADF) test) and with the smallest Akaike information criteria (AIC) (Hyndman & Khandakar, 2008). For the TS effect, I follow the suggestion of Chen and Liu (1993) to set the coefficient for the decaying impact (delta) at 0.7 for the procedure. However, whenever the procedure identified a TS effect, I modified delta by increment of 0.1 between 1 and -1 and chose the model with the smallest AIC.

Results

Table 4.1 compares the mean monthly counts of events for several gangs active within the safety zone by time period, along with the results of independent sample t-tests. Cells of the tables in grey indicate time periods and gangs targeted by the injunctions. Tables 4.2 and 4.3 break down the events by group and solo events.

When comparing the pre-ICG period to the ICG-Longos period, the main targeted gang, ICG, did not see a significant decrease in all, group or solo events. During the same period, SOS saw a small decrease in group events, ABZ saw a decrease in all and solo events, while 18th street saw a decrease in all types of events. For some gangs, we see an increase in the number of events during the period between the implementations of the ICG and Longos/Surenos CGI. Both, BP and WSL saw an increase in events during this period driven primarily by an increase in solo events.

These results do not offer much support for the notion that the ICG injunction had an immediate influence on the numbers of encounters between police and ICG members. Of the gangs that saw changes in the number of police encounters, none of them were targeted by the new injunction. However, it is interesting to note that two of the gangs that saw an increase in solo events—BP and WSL—would soon be targeted by the Surenos injunctions. It may be that

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officers of the LBPD were already working on building evidence to secure an injunction. Of course, these increases may have nothing to do with the injunctions at all, and may be simply the result of chance and/or other processes related to the activities of the gang.

When we examine the period following the implementation of the Longos/Surenos injunction, we see a notable decrease in events involving all gangs and almost all types of events. Most gangs—enjoined or not—saw their total number of encounters with the police, as well as group and solo events, decrease when we compare this time period to both the Pre-ICG and the ICG-Longos periods.

Table 4.1- Mean monthly counts of events by gang and time period

Gang	Pre-ICG Mean	SD	ICG-Longos Mean	SD	Change ICG-Pre t	p-value	Post-Longos Mean	SD	Change Longos-Pre t	p-value	Change Longos-ICG t	p-value
ICG	111.42	17.21	99.80	28.14	-1.60	0.12	62.97	18.29	-10.05	0.00	-5.21	0.00
RTC	35.39	8.97	33.00	11.32	-0.73	0.47	25.94	9.18	-3.84	0.00	-2.21	0.03
ABZ	17.69	5.78	12.93	4.74	-2.64	0.01	9.42	4.58	-5.92	0.00	-2.36	0.02
ESL	93.08	22.84	90.67	21.39	-0.33	0.75	60.16	15.12	-6.39	0.00	-5.45	0.00
WSL	14.69	5.17	15.60	4.79	0.54	0.59	11.77	4.35	-2.27	0.03	-2.65	0.01
BP	25.89	7.41	34.87	7.81	3.57	0.00	17.48	8.88	-3.76	0.00	-6.32	0.00
18th	17.92	6.97	8.53	3.20	-4.80	0.00	4.52	2.11	-9.99	0.00	-4.96	0.00
SOS	7.04	3.56	5.27	2.72	-1.63	0.11	2.32	1.73	-6.40	0.00	-4.35	0.00
TRG	9.89	5.06	8.00	3.97	-1.21	0.23	5.48	2.86	-4.05	0.00	-2.40	0.02

Table 4.2. Mean monthly counts of group events by gang and time period

	Pre-ICG		ICG-Longos		Change ICG-Pre		Post-Longos		Change Longos-Pre		Change Longos-ICG	
Gang	Mean	SD	Mean	SD	t	p-value	Mean	SD	t	p-value	t	p-value
ICG	33.27	6.92	29.33	13.03	-1.23	0.31	15.84	6.14	-9.89	0.00	-4.67	0.00
RTC	10.92	4.37	10.20	5.62	-0.45	0.68	7.68	3.86	-2.93	0.01	-1.74	0.14
ABZ	7.08	3.75	5.20	2.26	-1.72	0.06	2.68	1.79	-5.69	0.00	-4.02	0.00
ESL	28.08	9.81	26.80	9.63	-0.39	0.70	14.77	4.88	-6.52	0.00	-5.50	0.00
WSL	4.65	3.42	3.53	2.66	-1.07	0.26	3.13	2.23	-1.99	0.06	-0.53	0.63
BP	10.00	3.60	11.67	4.73	1.24	0.26	4.48	3.40	-5.84	0.00	-5.75	0.00
18th	6.42	4.17	3.07	1.91	-2.87	0.00	1.32	1.09	-6.43	0.00	-3.84	0.01
SOS	2.96	2.35	1.73	1.24	-1.84	0.04	0.81	0.82	-4.70	0.00	-2.96	0.02
TRG	3.81	2.69	2.73	1.29	-1.42	0.10	1.48	1.29	-4.19	0.00	-3.01	0.01

Table 4.3. Mean monthly counts of solo events by gang and time period

	Pre-ICG		ICG-Longos		Change ICG-Pre		Post-Longos		Change Longos-Pre		Change Longos-ICG	
Gang	Mean	SD	Mean	SD	t	p-value	Mean	SD	t	p-value	t	p-value
ICG	78.15	15.03	70.47	18.27	-1.42	0.19	47.13	13.48	-8.07	0.00	-4.77	0.00
RTC	24.46	7.07	22.80	8.83	-0.64	0.55	18.26	6.26	-3.45	0.00	-1.96	0.10
ABZ	10.62	2.66	7.73	3.28	-2.99	0.01	6.74	3.74	-4.34	0.00	-0.86	0.38
ESL	65.00	15.26	63.87	14.17	-0.23	0.82	45.39	11.11	-5.50	0.00	-4.71	0.00
WSL	10.04	2.94	12.07	3.04	2.05	0.05	8.65	3.04	-1.72	0.09	-3.50	0.00
BP	15.88	5.18	23.20	4.35	4.49	0.00	13.00	6.04	-1.88	0.06	-5.72	0.00
18th	11.50	3.99	5.47	2.22	-5.26	0.00	3.19	1.82	-10.18	0.00	-3.61	0.00
SOS	4.08	2.35	3.53	1.96	-0.74	0.45	1.52	1.27	-5.13	0.00	-4.10	0.00
TRG	6.08	3.01	5.27	3.13	-0.80	0.44	4.00	2.34	-2.88	0.01	-1.50	0.19

ARIMA and outlier detection

ICG vs RTC

Tables 4.4 and 4.5 present the results of the time-series outlier detection procedure for solo and group events involving ICG members. Table 4.4 reports the parameters for the time series for solo events involving ICG members. The only outlier detected by the procedure—a positive temporary change—happens to fall exactly on the first month the preliminary ICG injunction was implemented. This effect suggests that in the first months after the injunction was implemented the number of solo events involving ICG members increased and this effect continued in subsequent periods though the effect decreased by half (delta=0.5) for each subsequent month compared to the previous month. Figures 4.3 and 4.4 show—for solo and group event, respectively—the original time series (in black), the adjusted series without the outlier effects (in grey), and the outlier effects (in red) estimated by the models.

Table 4.4. ICG solo events regression with ARIMA (0,1,1)(1,0,0)[12] errors

	Coef.	SE	t-statistic
MA1	-0.88	0.05	-18.23
SAR1	0.56	0.11	5.03
TC-March 2010	45.67	9.20	4.97
delta	0.50		
AICc	569.47		

For ICG group events, the best fitting ARIMA model was an AR1 model with two additive outliers and one level-shift. The first additive outlier occurs several months before the preliminary ICG injunction (end of February 2010) was granted, therefore it is unlikely that this effect is due to the injunction. The procedure did not detect any effect on the time series around the date of the ICG injunction. That said, the procedure did detect a positive additive outlier in September 2010, followed by a negative level-shift in October of 2010. While these dates are far

removed from the implementation of the ICG injunction, it is interesting to note that the dates

occur around the timing of the signing of the NSL injunction (September 2010), but most

importantly, the public announcement of the new injunction by LBPD Chief McDonnell and City

Attorney Doug Haubert on November 8th 2010.

Table 4.5. ICG group events regression with ARIMA (1,0,0) errors

	Coef.	SE	t-statistic
Intercept	32.86	1.52	21.68
AR1	0.27	0.12	2.29
AO-August 2009	20.07	6.17	3.25
AO-September 2010	29.34	6.32	4.64
LS-October 2010	-15.92	2.04	-7.81
AICc	482.53		

Recall that the ICG injunction was never announced in the media, probably because it

was sought by the previous City Attorney and approved during a period of transition for the

LBPD Chiefs. In fact, the preliminary ICG injunction was approved only a few days before

Chief McDonnell was officially appointed. A possible explanation for the effect found in this

model may be that officers increased their enforcement of the ICG injunction around the time the

new NSL injunction was approved. It could also indicate a delayed effect of the injunction on

group behavior.

We can compare the results above with those obtained by models for RTC

members. Tables 4.6 and 4.7 present the results of the outlier detection procedure for RTC solo

events and group events, respectively. For solo events, the procedure did not detect any notable

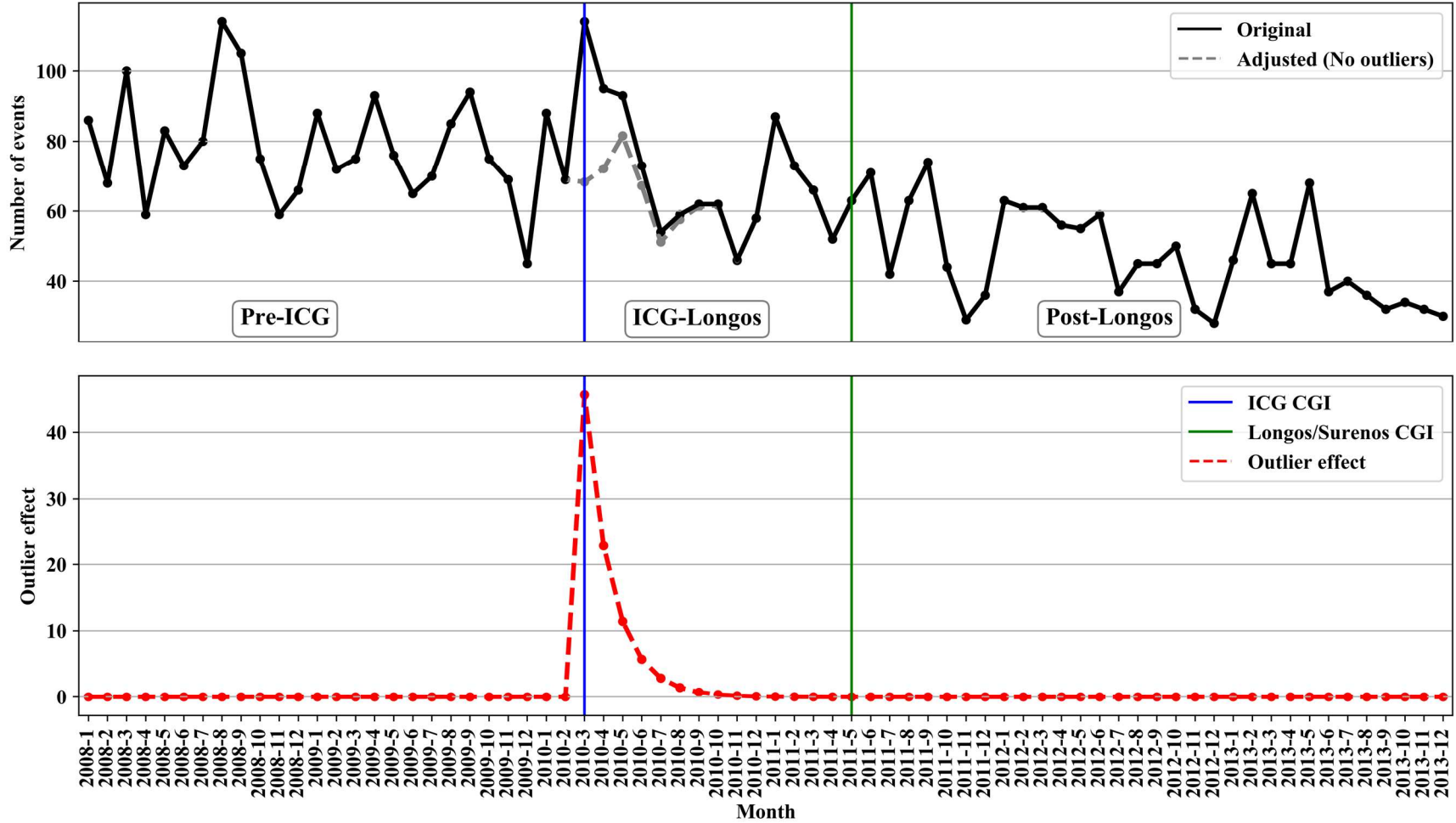outliers, which is what we should expect given that RTC was not under an injunction.

Figure 4.3. ICG solo events time-series (black), adjusted series (grey), and outlier effect (red)
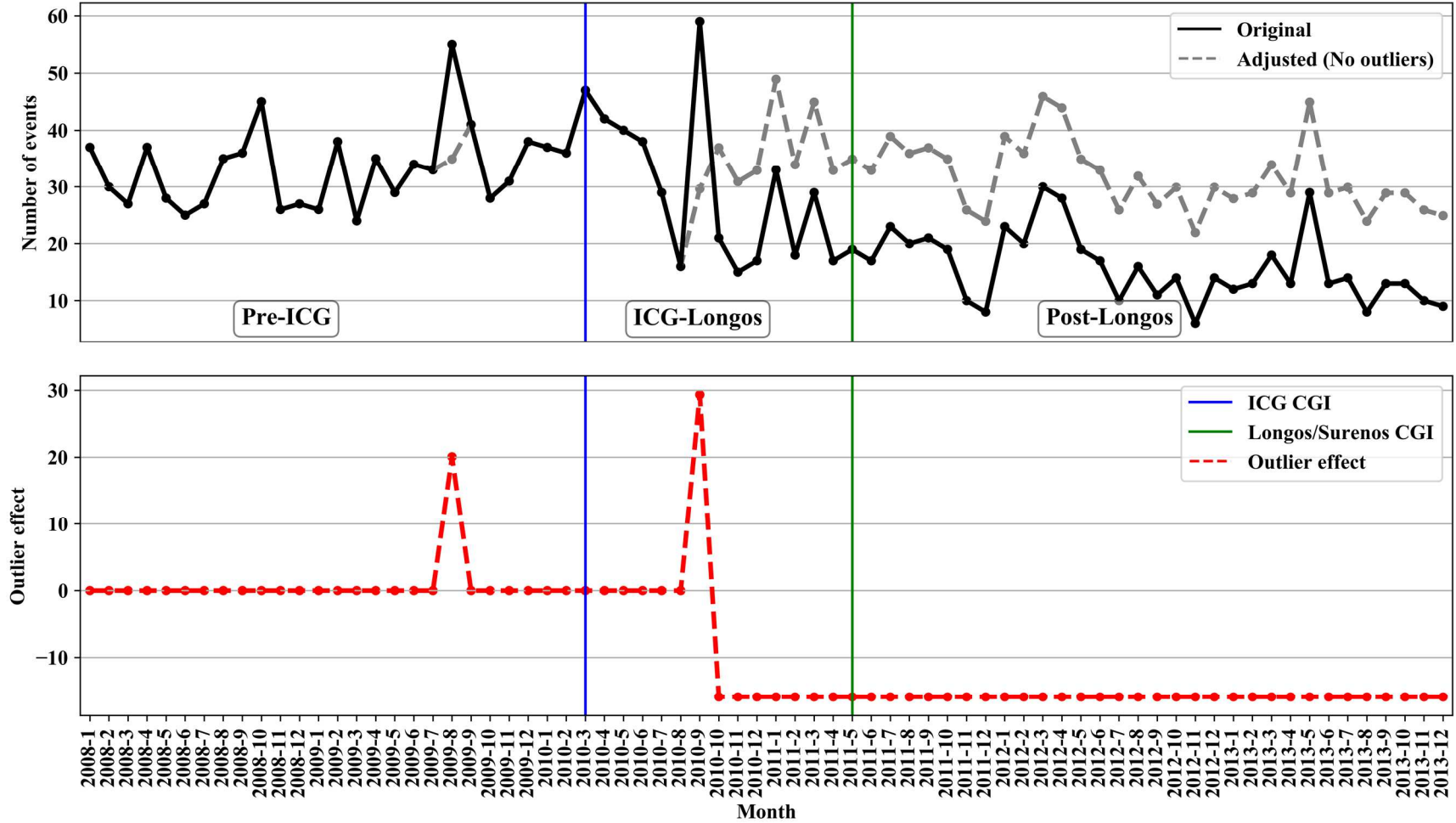
Figure 4.4. ICG group events time-series (black), adjusted series (grey), and outlier effect (red)

Table 4.6. RTC solo events regression with ARIMA (0,1,1) errors

	Coef.	SE	t-statistic
MA1	-0.90	0.06	-15.43
AICc	493.44		

Table 4.7. RTC group events regression with ARIMA (0,1,1) errors

	Coef.	SE	t-statistic
MA1	-0.89	0.07	-12.14
AO-September 2010	14.62	4.21	3.47
AICc	417.16		

For group events (Table 4.7 and Figure 4.5), we find a single outlier—a positive additive outlier in September 2010, the same time as one of the additive outlier found for ICG group events. The fact that both ICG and RTC group events increased at the same time might suggest that a similar process affected the observation of group events for both gangs around that time. One possibility may be that in preparation for the public unveiling of the new injunction program, LBPD officers increased their enforcement of all active gang injunctions. The fact that RTC, a gang not under any injunction, saw an increase in group events may be the results of a net-widening effect associated with the aggressive enforcement of the ICG injunction. RTC is African American Crips gang active in the same general area of the city as ICG, may have been targeted by officers seeking to enforce the ICG injunction, even though RTC were not under an injunction. This might explain why for RTC group events this sudden increase is followed by a return to the average level of the time series, whereas for ICG group events, the spike in group events in September 2010 is followed by a permanent negative level shift in group events. This may suggest that while both gangs were targeted by the increase enforcement efforts, only the gang that was actually targeted by a CGI modified its behavior. The nature of the data makes it

impossible to know whether this effect is a result of police behavior or a reaction on the part of the enjoined gang.

Surenos vs. Asian and Pacific Islander gangs

For this set of analysis, I compare solo and group events involving any members of the main Surenos groups active in the safety zone—ESL, WSL, BP, and 18th street—to the events involving Asian and Pacific Islander gangs—ABZ, SOS, and TRG—that were not targeted by injunctions during the same period.

Tables 4.8 and 4.9 present the ARIMA models with outliers for solo events and group events involving Sureno groups, respectively. Figures 4.6 and 4.7 show a graphical representation of the results for solo events and group events involving Sureno groups, respectively. For solo events, the procedure identified three potential interventions on the time series: a positive additive outlier in March 2010, a negative level shift in May 2011, and a negative additive outlier in December 2011. Interestingly, the March 2010 additive outlier occurred around the same month as the implementation of the ICG injunction. This may suggest that a similar process is responsible for a temporary increase in the number of solo events for Surenos and ICG members. The negative level shift that occurred in May 2011 lines up with the implementation of the Longos/Surenos injunction. The fact that solo events decrease runs counter to the hypothesis that the implementation of a CGI would lead to an increase in solo events due to officers attempting to serve members with the condition of the court order. Finally, the last outlier, a negative additive outlier in December 2011 is difficult to interpret given its distance to any intervention.

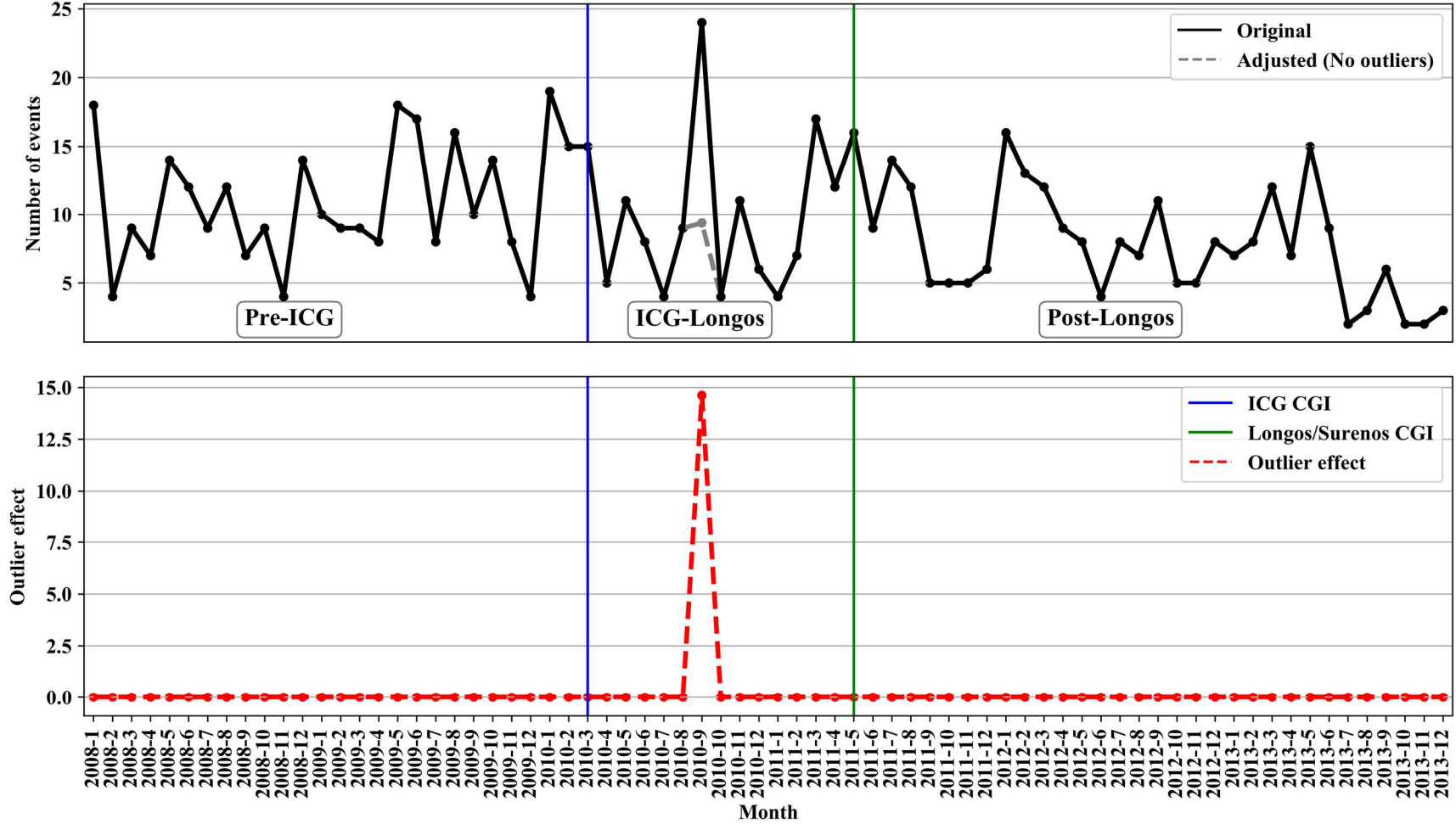Figure 4.5. RTC group events time-series (black), adjusted series (grey), and outlier effect (red)
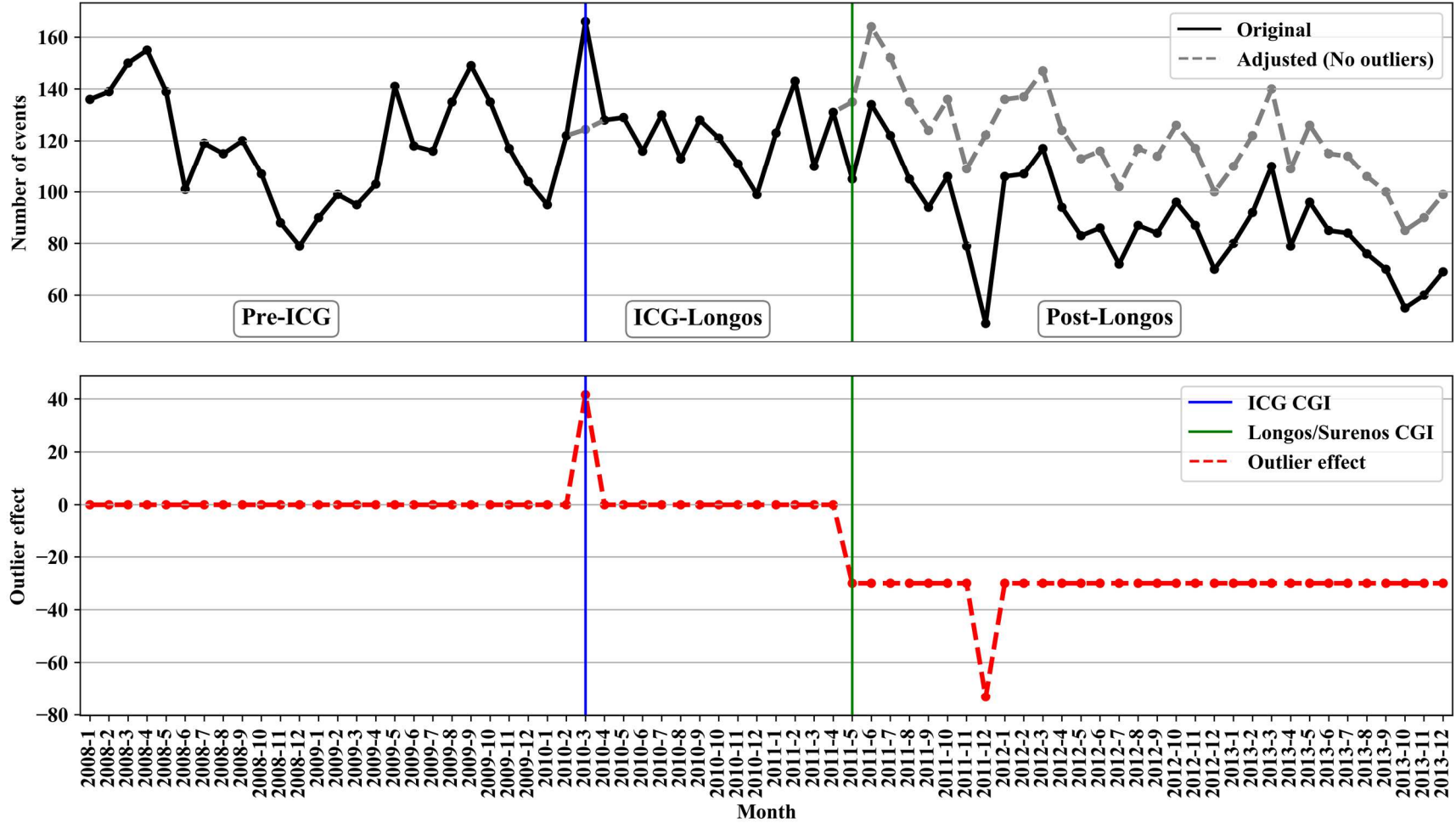
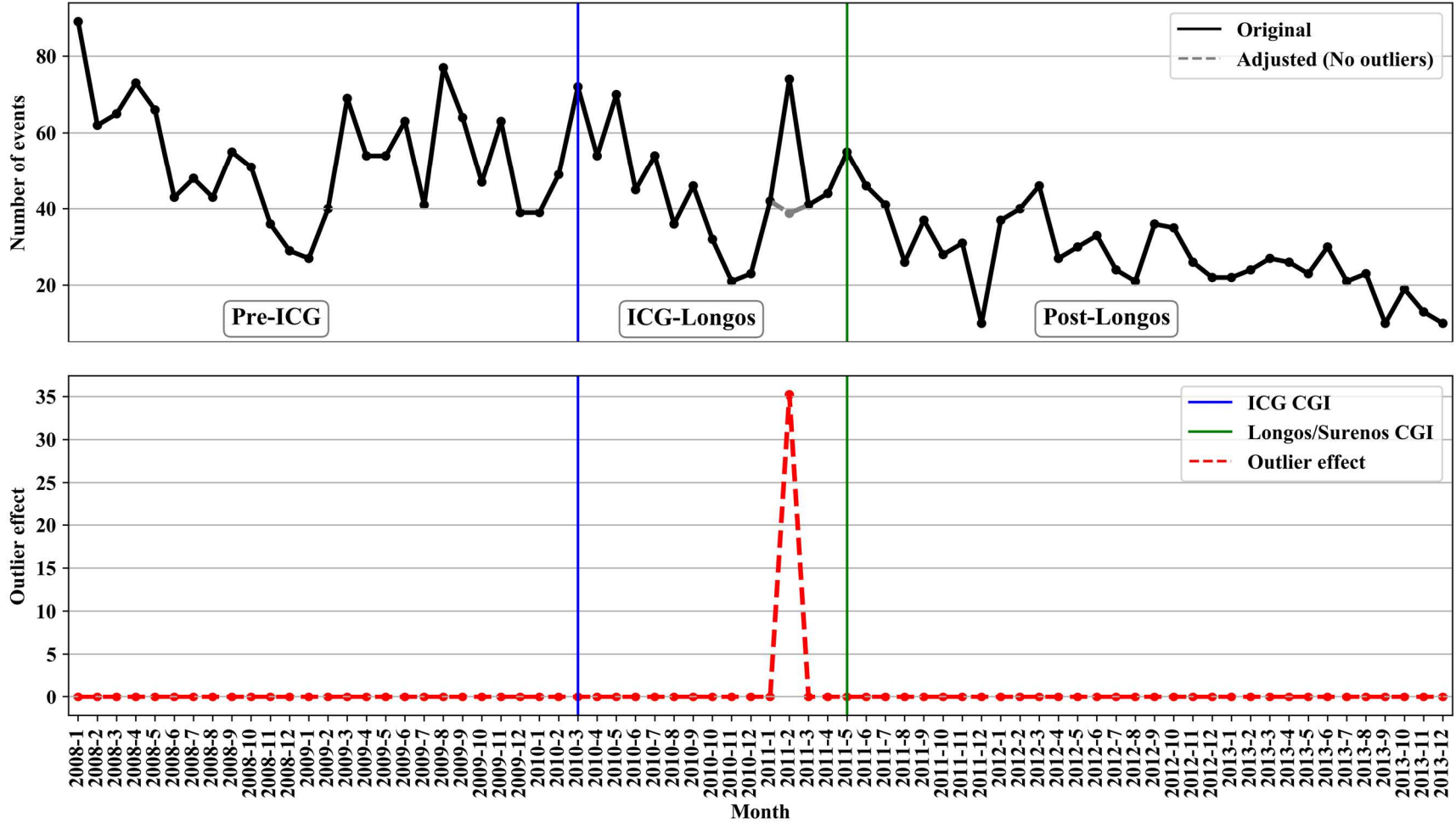Figure 4.6. Sureno solo events time-series (black), adjusted series (grey), and outlier effect (red)

Figure 4.7. Sureno group events time-series (black), adjusted series (grey), and outlier effect (red)

Table 4.8. Surenos solo events regression with ARIMA (1,0,0) errors

	Coef.	SE	t-statistic
Intercept	119.58	5.39	22.19
AR1	0.61	0.09	6.55
AO-March 2010	41.60	12.07	3.45
LS-May 2011	-30.01	7.62	-3.94
AO-December 2011	-43.17	12.07	-3.58
AICc	599.30		

Table 4.9. Surenos group events regression with ARIMA (0,1,1) errors

	Coef.	SE	t-statistic
MA1	-0.44	0.13	-3.36
AO-Febuary 2011	35.21	10.41	3.38
AICc	560.22		

For group events, an additive outlier was detected in February 2011, which reflects a positive spike in the time-series at that particular point in time. Once again, it is difficult to attribute this effect to the injunction because it occurs several months before the implementation of the injunction, though it could be reflective of an increase in police attention to the gang in preparation for the filing of the injunction in court.

The last two sets of models are presented in Tables 4.10 and 4.11 (Figure 4.8) for solo and group events involving Asian and Pacific Islander gangs. The procedure does not identify any significant changes in solo events for these gangs, while it identified several changes that predated the Surenos injunction. There may be something particular to these gangs that explains the high variability in group events in 2008 and 2009. However, there is no indication that the time-series shows any substantial variation around the time of the implementation of the injunctions, which is what we would expect given that these gangs were not targeted by any CGIs yet.
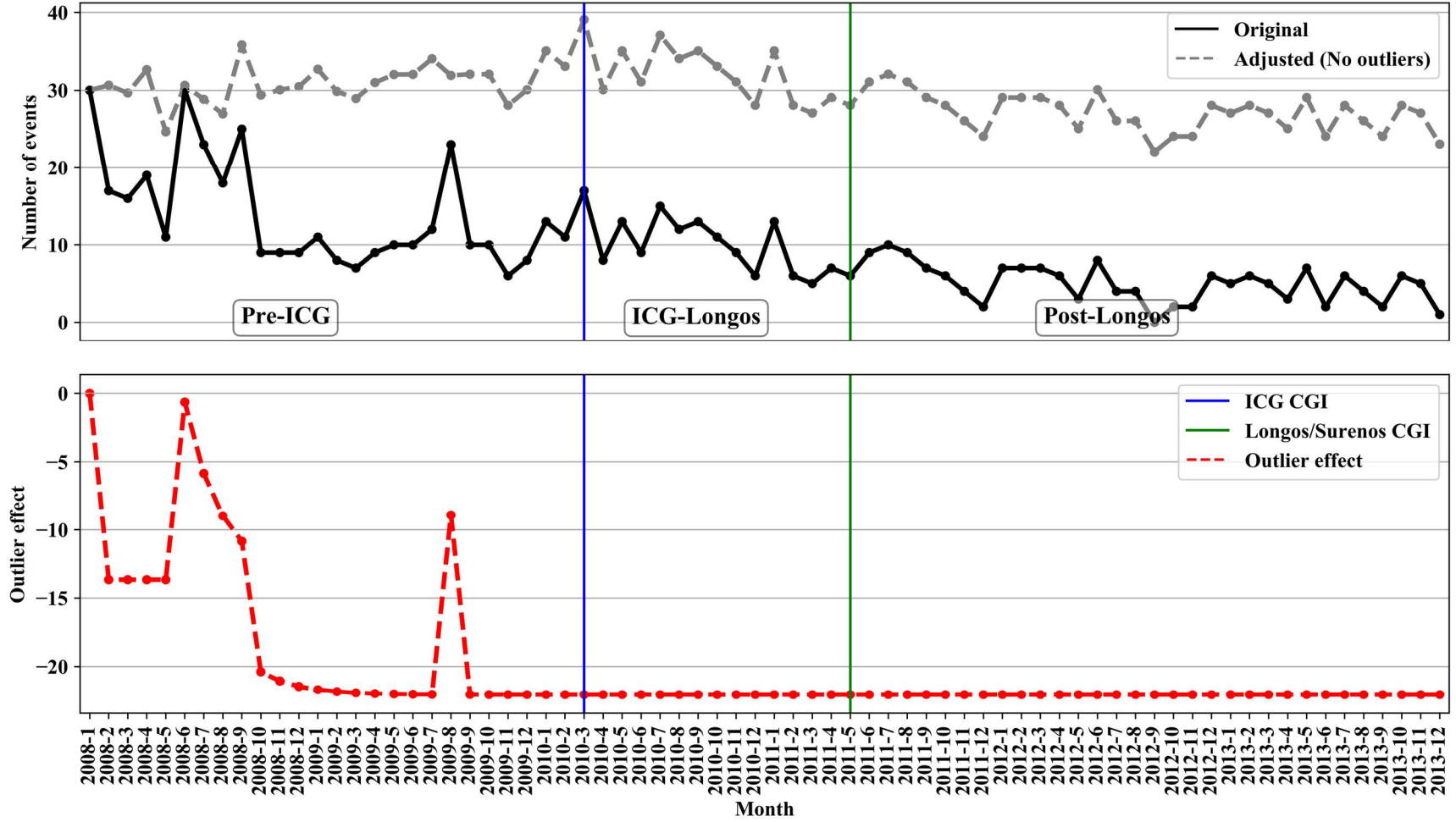
Figure 4.8. Asian/Pacific Islanders group events time-series (black), adjusted series (grey), and outlier effect (red)

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Table 4.10. Asian and Pacific Islander solo events regression with ARIMA (0,1,2) (1,0,0)[12] errors

	Coef.	SE	t-statistic
MA1	-0.61	0.14	-4.26
MA2	-0.24	0.14	-1.70
SAR1	0.30	0.13	2.23
AICc	445.52		

Table 4.11. Asian and Pacific Islander group events regression with ARIMA (0,1,1) errors

	Coef.	SE	t-statistic
MA1	-0.76	0.08	-10.09
LS-Febuary 2008	-13.66	2.75	-4.97
TC-June 2008	13.02	2.60	5.01
LS-October 2008	-8.42	1.98	-4.25
AO-August 2009	13.16	2.54	5.19
delta	0.60		
AICc	356.89		

Discussion

As anticipated, the available data makes it difficult to disentangle effects that represent LBPD's efforts to document gang activity, serve individual members with the conditions of the injunction, and enforce the conditions of the injunction, and those that represent the targeted gangs' reactivity to the implementation of the injunction. Generally, the results above do not provide any conclusive evidence that would allow me to conclude that CGIs influenced group behavior in Long Beach. What the models above do show however is that events involving gang members appear to have generally decreased in the period following the implementation of the Surenos injunctions in 2010 and 2011. The decrease is not limited to gangs targeted by the injunctions, as the mean number of monthly events for every gang I examined decreased from the pre-ICG and pre-Longo CGI time period. Furthermore, given the analysis of the previous chapter, it is unclear whether this decrease is in fact due to CGIs, or the general downward trend

in arrest and FI records that may be attributed to changes in policing practices and other legal changes. The only way to attribute these changes to the CGIs is to show that changes in the number of group and solo events occur around the time where injunctions were implemented, and that these changes mostly affected groups targeted by the CGIs.

The analyses of time-series conducted revealed that several abrupt changes did occur on and around the time of the implementation of the multiple CGIs. I had hypothesized that we might see an increase in solo events in the months leading up to and immediately after the implementation of the CGIs, which would be an indication that the fluctuation in the time series is more a result of police behavior than a reaction from the gang to the policy. Following the implementation of the ICG injunction, this is precisely what the analysis showed: A sharp increase in the number of solo ICG events in the first month when the CGI was active (March 2010), followed by a gradual decay and a return to the average level. Interestingly, while I did not identify any significant increase in the main comparison group, the RTC gang, I did identify a similar effect at the exact same time for the Surenos.

It is unclear why the Surenos, who would only be targeted by injunctions several months later, saw an increase in solo events at the exact same time. It may be a coincidence, though it should be noted that March of 2010 was an eventful period for the LBPD with a change in police chief occurring at the same time as the ICG injunction was implemented, which could have influenced the collection of records on some of the largest and most active gangs in Long Beach. Similarly, the availability of a new injunction as an enforcement tool for LBPD officers may have been associated with a "revival" of the old ESL and WSL injunction granted in the early-to-mid 2000s. Since these CGIs were permanent, it is possible that the implementation of the ICG

injunction prompted officers to start using the old ESL and WSL injunctions again, which could account for an increase in Surenos solo events.

The influence of the Longos/Surenos CGI on solo events did not have the hypothesized effect. Instead, the analysis revealed a permanent level-shift in the number of solo events beginning the first months the CGI became active (May 2011), suggesting that unlike for ICG injunction, there is no evidence that police ramped up their targeting of Surenos members for the purpose of either documenting members and serving them with the conditions of the injunction. One hypothesis as to why this effect differed from the ICG injunction may be that these efforts occurred over a longer time period in concert with the preparation and enforcement of the ICG and NSL injunctions implemented in relatively short succession in 2010. It could also suggest that Surenos members, who were also targeted in the NSL injunction in North Long Beach, had time to modify their behavior after seeing other Surenos gang members being enjoined and targeted. Furthermore, unlike for the ICG injunction, the newly appointed Chief and newly elected City Attorney announced the two Surenos injunctions publically in the media.

As for variations in group events, it is difficult to attribute the effects identified to the CGIs. Curiously for both ICG and RTC gang members, the analysis revealed an increase in group events several months after the implementation of the ICG injunctions, in September 2010. It is unclear what could have caused this increase but the fact that both gangs saw an increase at the same might could suggest that it is related to a change on the enforcement side. That said, ICG group event—but not for RTC—did decrease significantly in the months following this spike, which could indicate that ICG members did modify their behavior as a result of the injunction.

Implications for social network analysis of police data

While the implementation of several CGIs occurring in the middle of the study period gave me an interesting opportunity to explore the influence of these policies on gang group behavior, the primary reason to examine the effect of CGIs in the context of this dissertation was to determine whether changes in group events had more to do with police behavior rather than gang behavior. Contrary to what Valasik (2014) found in the context of FI cards, I believe that the analyses of this chapter show compelling evidence that CGIs have as much, if not more, an influence on how police target and engage in stops with gang members. While the influence is particularly evident in sudden increases in solo events, which would not necessarily impact the structure of networks because, it could be that by spending more time trying to identify and target members of an enjoined gang, less attention is spent on other gangs. This could explain the reduction in both solo and group events for all gangs—even those that were never enjoined during the time period—in the later years of the study period. Of course, we cannot rule out the fact that the deterrent effect of the CGIs could have affected other groups that were not targeted given that the areas where those gangs are active also included within the safe zones.

As I have mentioned at the outset of this dissertation, one area where networks from police data hold the most promise is in the study of street gangs. The analyses of this chapter suggest that researchers should investigate to what extent policies such as CGIs affect the work of officers patrolling the streets, and how this may lead to a reduction or increase in records of group events. An important limitation of this chapter is that it was impossible for me to directly observe how officers use investigative tools such as FI stops in the context of enforcing CGIs or even in preparation to submit documents to secure a CGI. Future research should investigate how officers may change their routines and record-keeping practices in these contexts.

CHAPTER 5. CONCLUSIONS AND FUTURE DIRECTIONS

The purpose of this dissertation was to examine the implications of using police data to construct social networks. To do so, I examined six years of arrest and FI records from the Long Beach Police Department. Chapter 2 describes the process of extracting relational and individual level data from FI and arrest records, and describes their composition. An important observation I made during this process was that most relationships (55.31%) in the co-arrest network came from events where the most serious crime committed was a minor offense such loitering, drinking in public, curfew violations, public nuisances, truancy, trespassing, bicycle and pedestrian violations, destruction of property (graffiti, possession of tools for graffiti), and fare violations. An additional 14.05% came from drug offenses, which analyses in Chapter 3 revealed to be largely made up of minor possession of marijuana.

Studies using co-arrest data do not always provide a description of the types of crime from which relationships are extracted, but information from those that do suggest that the current study is not unique in this regard. For example, Charette and Papachristos (2017) report that 58.4% of ties in their network came from "offenses against the administration of justice (e.g. breach of probation, disturb the peace)" (p. 7). In another study, Papachristos et al. (2015) used, in addition to arrest and FI records, citations for QOL ordinance violations, which unlike for Long Beach were kept separately from arrest records in Newark, New Jersey. Although they do not report the number of relationships that come from each dataset separately, the authors note that while 35.6 % of individuals had at least one tie from arrests, 34.9% had at least one tie from QOL citations.

An implication of the fact that most relationships in the network come from offenses like loitering, drinking in public, and curfew violations is that the structure of a co-arrest network

depends as much on the propensity of individuals in a community to hang out on street corners and public parks, as it does on the police's focus on these public spaces. This is important for understanding the data-generating process and how it can vary over space (geographical *and* social) and time, but perhaps also as an alternative explanation for some of the recent findings using similar data.

First, co-arrest and co-FI data are probably far more sensitive to the way police conduct their work than network researchers have been willing to admit. It is true that as Papachristos et al. (2015, p.635) put it "the usual caveats associated with the use of official police data in criminological research circumscribe the data we use [...] such as bias introduced by police decision-making process". It is also true that a typical limitation of network analysis of police data is that we might be missing nodes and ties of individuals crafty enough to avoid the police (e.g. Morselli, 2009). But these limitations may pale in comparison to the influence of deliberate policing strategies that specifically target QOL offenses (e.g. Wilson & Kelling, 1982) or even hot-spot policing (e.g. Braga, 2001; Ratcliffe, Taniguchi, Groff, & Wood, 2011). If relationships in co-arrest networks depend so much on crimes that, unlike most serious crime, are observed first hand by patrol officers, any temporal and spatial changes in the concentration of police patrol should have an influence on the structure of networks, regardless of the actual behavior on individuals we find in these networks.

Second, if the connectivity of a co-arrest network depends so much on QOL offenses, which are by definition public offenses, it may be provide an alternative explanation for the social contagion argument of violent victimization (e.g. Green, Horel, & Papachristos, 2017; Papachristos, Wildeman, & Roberto, 2015). It may be that visibility in public spaces explains

both network connectivity (or the likelihood of being found in the main component[9] as most studies on the topic limit their analysis to this part of the network) and the likelihood to get shot. It may be possible to test this assumption empirically by testing whether involvement in QOL arrests increases ones likelihood of victimization.

Third, given the importance of disproportionate importance of QOL offenses in co-arrest networks, we must consider that some of the better connected individuals in the network may be those most likely to be repeatedly arrested for various public nuisance offenses: the homeless. It may be possible to examine this aspect of the network in future work using the narrative of FI cards to identify transient individuals. In preliminary analyses of the community structure (i.e. dense clusters in the network) of the network, I was able to find multiple clusters that had higher concentrations of gang members, typically of the same groups or falling under the same umbrella (e.g. Crips, Longos, Pacific Islanders). Throughout my experiments with several algorithms, a consistent finding was that one of the community that emerged was a very large and relatively dense cluster with very few gang members compared to other communities, with a higher than average rate of QOL offenses. I believe that this dense community actually represents a community of homeless individuals in the city. Future efforts will be devoted to examine this aspect of the network more in-depth. It may be logical to expect that of all the individuals in found in co-arrest networks, the homeless would be among those whose ties are most likely to be captured in these records given their frequent, often negative interactions with the police, as recently suggested by Stuart (2018).

Another type of relationship that contributes a non-trivial proportion of the connectivity in co-arrest networks comes from minor possession of marijuana. Of course, arrests for

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[9] The largest part of the network in which all nodes are directly or indirectly connected

marijuana possession may very well be occur in similar contexts as QOL offenses (Geller & Fagan, 2010). However, with recent trends across the United States towards decriminalization and even legalization of recreational marijuana, researchers should consider how changes in the enforcement of these offenses impact the relationships they observe in their networks. Although marijuana is now, since January 2018, legal for recreational use in California, in 2008, at the beginning of the study period, minor possession of marijuana was still a misdemeanor offense someone could be arrested, go to court, and potentially be fined up to $100. In 2010, the law changed only slightly so that a violation would amount to the equivalent of traffic ticket. In Chapter 3, I argued that the incremental change toward legalization may have led officers to reduce their enforcement of marijuana possession. An offence that generated over 1800 events in 2008 generate barely over 400 events by 2013. Although it is not impossible, it seems unlikely that the reduction is actually a result of a drastic change in behavior.

Chapter 3 also examined a potential source of variation in the composition of FI events: California's Public Safety Realignment. The policy shifted a significant proportion of the state prison population toward county jails and community supervision and was met with claims of "doom and gloom" by law enforcement officials across the State, including in Long Beach. As researchers continue to unpack the effects of such a major policy shift, it may be interesting to examine in more depth how police department reacted to the policy.

Finally, to conclude on the results of Chapter 3, it may well be that the variations in police records I observed are quite unique to the policing environment and policy context of Long Beach and California more broadly. However, I would venture that all police departments have to adapt to ever-changing financial, political, and social contexts. Although one may disagree with the particular sources of variations I outline, what this study makes clear is that

there is substantial variation in the types of records that generate a large proportion of relationships in co-arrest networks. As I have noted in the conclusion of Chapter 3, longitudinal analyses of co-arrest data have been rare, and I would probably advise against it unless it is preceded by a thorough examination regarding the stability of the data generating process. That said, variations over time in the data generating process might influence even cross-sectional analyses of network data particularly given the fact that most analyses of co-arrest networks combine several years of data. For instance, the number of connection a node has may be more tied to fact that this individual was more active at a time and in an area where police engaged in aggressive enforcement of QOL offenses rather than to that person's actual behavior.

Chapter 4 examined the influence of gang injunctions on their members' patterns of association. The results do not show convincing evidence that CGIs in Long Beach actually had an influence on the behavior of gang members. There is more convincing evidence that police officers changed their behavior for the purpose of preparing and enforcing the injunctions. This finding would add to the findings of chapter 3 regarding the influence of policing on the composition of police records. Of course, future research should more directly test the notion that police officers modify their behavior as a result of the implementation of CGIs through direct observations of police work. Similarly, regarding the influence of injunctions on gang behavior, future research should try to collect data independent from the enforcement of these injunctions, either through field observations or interviews with gang members. It is very difficult to untangle the different processes involved in the creation of FI and arrest records in this context, a difficult noted previously by Valasik (2014).

The multiple sources of variations in the data generating process behind records used for SNA highlight the need for scholars to be aware of any major changes that occur during the

period covered by the data. The vast majority of studies using co-arrest and co-FI networks combine together several years of data. The more years a study combines, the greater the chances that external factors might influence the data generating process. Under these circumstances, it becomes difficult to know whether some structural features of the network or the position of individuals in these networks are related to the behavior of the police or of the individuals in the network.

For example, conclusions regarding the structure of relationships within and between street gangs in Long Beach may be very different if we were to look at the networks in 2008 and 2009, compared to those in 2012 and 2013. As a result, groups active in the earlier years may be easier to identify using community detection algorithms compared to those active in later years because of a higher density of ties between members of the same group. A sharp reduction of ties is likely to be especially problematic for the identification of ties *between* groups. Compared to ties within groups, such relationships are more rare and therefore more difficult to observe, but can be quite important to understand diffusion processes.

At the individual-level, changes in the likelihood of observing relationships due to changes in the data generating process might influence our interpretation of basic measures of centrality. Individuals active in 2008 may have a higher number of ties than someone active in 2013, not necessarily because they are better connected to other offenders in Long Beach, but because police officers were more likely to arrest individuals involved in QOL offenses in 2008 than in 2013.

Generally speaking, researchers should be mindful of the nature of nodes and edges that are uncovered through police work when designing their studies. These networks represent for the most part publicly visible activities and individuals who engage in such public activities. For

these reasons, co-arrest and co-FI networks may be especially useful to study research questions related to behavior that are public in nature such as gang behavior and gun violence. That said, researchers should consider using shorter time periods when combining several years of data. This practice would avoid some of the issues related to the data generating process I have explored in this dissertation.

Future directions

There is much to do regarding before I can answer the question of whether we should use police data to study criminal networks. Perhaps more importantly, researchers should spend a lot more time thinking about the types of relationships that are relevant to criminal behavior and better defining what it is that co-arrest and co-FI ties are capturing. Morselli (2009) summarized some of the critiques waged at SNA by quoting Marcus Felson. Felson argued that:

> "a social network for crime, as important as it might be, generates a serious problem, since a network has no clear boundaries and is difficult to measure, analyze, or use to predict what happens on the ground. Somebody has got to specify the facts about a delinquency network and show that it has an ongoing structure producing criminal cooperation" (quoted in Morselli, 2009, p.169)

Throughout my work on my dissertation, I have thought a lot about Felson's critique and it is difficult to disagree with him. In the introduction, I discussed the work done by Sarnecki (1990) to assess the extent of missing ties through interviews. I believe that a relatively simple next task for researchers is to replicate Sarnecki's study and conduct interviews with individuals that are found in these co-arrest networks, map their personal networks and compare these relationships to those found in the networks.

Generally, I believe criminologists need to get out in the communities they study and collect relational data directly. This may be very challenging, but even limited efforts in doing so would enlighten us as to what we are actually seeing in co-arrest and co-FI data. Focusing on

street gangs may be a good starting point as it may be easier to delineate and identify the relevant individuals to talk to. Gang researchers go through painstaking efforts to measure the influence of gang structure and group processes using data collected at the individual level when social network analysis provides the proper tools to directly study many of these questions. For instance, in recent years, gang researchers have grown more and more dissatisfied with the binary world they have been operating in for the past several decades. Recognizing that gang membership *must* be more complex than the typical dichotomous indicator that has served them so admirably for years, scholars have begun advocating employing continuous measures of membership such as indicators of "gang embeddedness" (e.g. Pyrooz, Sweeten, & Piquero, 2013). Pyrooz et al. (2013) drew from Hagan's (1993) concept of criminal embeddedness—who himself borrowed the notion of embeddedness from Granovetter's work (1983)—to define gang embeddedness as an individual's immersion in deviant social networks, "reflecting varying degrees of involvement, identification, and status among gang members—the adhesion of the gang member to the gang" (p.243). Essentially, measures of social embeddedness—whether criminal or gang—treat involvement in a certain social networks as falling along a continuum. Measures of gang embeddedness have typically been constructed without direct access to data on patterns of associations. However, they tend to use proxy measures that attempt to capture individual social closeness to the gang such as the frequency of interaction with other members, the proportion of friends in the gang, and the one's position within the gang (Decker, Pyrooz, Sweeten, & Moule, 2014). In the future I hope to examine whether co-arrest and co-FI networks could be used to study gang embeddedness, but of course, it would be ideal to obtain relational data through interviews for that purpose.

As James F. Short (2009, p.728) once wrote about the use of police databases for the purpose of studying gangs: "The police should not be expected to perform systematic studies of youth collectivities, whether they are called gangs or something else. Such research is the job of scholars, independent of policy burdens." The future of a network perspective in criminology will depend on the ability and willingness of researchers to move away from official data and go out and collect their own. It is impossible to assess how valid, accurate, or even just "good enough" arrest and FI data are to the study of crime without something to compare it to.

REFERENCES

Aaronson, D. E., Dienes, C. T., & Musheno, M. C. (1978). Changing the public drunkenness laws: The impact of decriminalization. *Law and Society Review*, *12*(3), 405-436.

Allan, E. L. (2004). *Civil gang abatement: The effectiveness and implications of policing by injunction.* El Paso, TX: LFB Scholarly Publishing.

American Civil Liberties Union (1997). *False premises, false promises: The Blythe street injunction and its aftermath.* Los Angeles, CA: ACLU Foundation of Southern California.

Baker, W. E., & Faulkner, R. R. (1993). The social organization of conspiracy: Illegal networks in the heavy electrical equipment industry. *American Sociological Review*, 58(6): 837-860.

Beck, K. H., & Summons, T. G. (1984). Police officer attitudes toward Marijuana: A replication and confirmation. *The American Journal of Drug and Alcohol Abuse*, *10*(4), 519-528.

Bittner, E. (1967). The police on skid-row: A study of peace keeping. *American Sociological Review*, *32*(5), 699-715.

Black, D. J. (1970). Production of crime rates. *American Sociological Review*, *34*(4), 733-748.

Blankstein, A. & Barboza, T. (2010, February 4). LAPD's McDonnell takes top post in Long Beach department. *Los Angeles Times*. Retrieved from http://www.latimes.com.

Blumstein, A., Cohen, J., & Rosenfeld, R. (1991). Trend and deviation in crime rates: A comparison of UCR and NCS data for burglary and robbery. *Criminology*, *29*(2), 237-263.

Borgatti, S. P., Everett, M. G., & Johnson, J. C. (2013). *Analyzing social networks*. New York, NY: SAGE Publications.

Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network analysis in the social sciences. *Science*, *323*(5916), 892-895.

Bouchard, M. & Malm, A. (2016). Social network analysis and its contribution to research on crime and criminal justice. In *Oxford Handbooks Online.* Retrieved from http://www.oxfordhandbooks.com/view/10.1093/oxfordhb/9780199935383.001.0001/oxfordhb-9780199935383-e-21.

Box, G. E., & Tiao, G. C. (1975). Intervention analysis with applications to economic and environmental problems. *Journal of the American Statistical Association*, *70*(349), 70-79.

Braga, A. A. (2001). The effects of hot spots policing on crime. *The ANNALS of the American Academy of Political and Social Science*, *578*(1), 104-125.

Bratton, W. J., & Kelling, G. L. (2015). Why we need broken windows policing. *City Journal*, Retrieved from https://www.city-journal.org/html/why-we-need-broken-windows-policing-13696.html.

Bratton, W. J., & Malinowski, S. W. (2008). Police performance management in practice: Taking COMPSTAT to the next level. *Policing: A Journal of Policy and Practice*, *2*(3), 259-265.

Bright, D., Koskinen, J., & Malm, A. (2018). Illicit network dynamics: The formation and evolution of a drug trafficking network. *Journal of Quantitative Criminology*, 1-22. https://doi.org/10.1007/s10940-018-9379-8

Brownfield, D., Sorenson, A. M., & Thompson, K. M. (2001). Gang membership, race, and social class: A test of the group hazard and master status hypotheses. *Deviant Behavior*, *22*(1), 73-89.

Brunson, R. K. (2007). "Police don't like black people": African-American young men's accumulated police experiences. *Criminology & Public Policy*, *6*(1), 71-101.

Brunson, R. K., & Weitzer, R. (2009). Police relations with black and white youths in different urban neighborhoods. *Urban Affairs Review*, *44*(6), 858-885.

Burgess, R. L., & Akers, R. L. (1966). A differential association-reinforcement theory of criminal behavior. *Social problems*, *14*(2), 128-147.

Bursik, R. J. & Grasmick, H. G. (1993). *Neighborhoods and crime: The dimensions of effective community control.* Lanham, MD: Lexington Books.

Caldwell, B. (2009). Criminalizing day-to-day life: A socio-legal critique of gang injunctions. *American Journal of Criminal Law*, *37*(3), 241-290.

Carr, P. J., Napolitano, L., & Keating, J. (2007). We never call the cops and here is why: A qualitative examination of legal cynicism in three Philadelphia neighborhoods. *Criminology*, *45*(2), 445-480.

Carr, R., Slothower, M., & Parkinson, J. (2017). Do gang injunctions reduce violent crime? Four tests in Merseyside, UK. *Cambridge Journal of Evidence-Based Policing*, *1*(4), 195-210.

Carrington, P. J. (2009). Co-offending and the development of the delinquent career. *Criminology*, *47*(4), 1295–1329.

Carrington, P. J. (2011). Crime and social network analysis. In Scott, John & Carrington, Peter J. (Eds.), *The SAGE handbook of social network analysis* (pp. 236–255). Thousand Oaks, CA: SAGE Publishing.

Charette, Y., & Papachristos, A. V. (2017). The network dynamics of co-offending careers. *Social Networks*, *51*, 3-13.

Chen, C., & Liu, L. M. (1993). Joint estimation of model parameters and outlier effects in time series. *Journal of the American Statistical Association*, *88*(421), 284-297.

Chen, C., & Tiao, G. C. (1990). Random level-shift time series models, ARIMA approximations, and level-shift detection. *Journal of Business & Economic Statistics*, *8*(1), 83-97.

City of Long Beach (2011). FY 12 adopted budget-Police. Retrieved from http://www.longbeach.gov/globalassets/finance/media-library/documents/city-budget-and-finances/budget/budget-documents/fy-12-adopted-budget-webpage/29-police

City of Long Beach (2012). FY 13 adopted budget-Police. Retrieved from http://www.longbeach.gov/globalassets/finance/media-library/documents/city-budget-and-finances/budget/budget-documents/fy-13-adopted-budget-webpage/29-police

City of Long Beach (2013). FY 14 adopted budget-Police. Retrieved from http://www.longbeach.gov/globalassets/finance/media-library/documents/city-budget-and-finances/budget/budget-documents/fy-14-adopted-budget-webpage/30-police

City of Long Beach (2014). FY 15 adopted budget-Police. Retrieved from http://www.longbeach.gov/globalassets/finance/media-library/documents/city-budget-and-finances/budget/budget-documents/fy-15-adopted-budget-webpage/police

City of Long Beach v. West Coast Crips. Los Angeles Case No. NC021240 (Cal. Super. Ct. Los Angeles County, 1997).

City of Long Beach v. Westside Longos. Los Angeles Case No. NC17601 (Cal. Super. Ct. Los Angeles County, 1995).

Cloward, R. A., & Ohlin, L. E. (1960). *Delinquency and opportunity: A study of delinquent gangs*. Glencoe, IL: Free Press.

Cohen, A. (1955). *Delinquent boys: The culture of gang*. Glencoe, IL: Free Press.

Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review*, *44*(4), 588–608.

Conway, K. P., & McCord, J. (2002). A longitudinal examination of the relation between co-offending with violent accomplices and violent crime. *Aggressive Behavior*, *28*(2), 97-108.

Crank, J. P. (1990). The influence of environmental and organizational factors on police style in urban and rural environments. *Journal of Research in Crime and Delinquency*, *27*(2), 166-189.

Curry, G. D. (2010). From knowledge to response and back again: Theory and evaluation in responding to gangs. In R. J. Chaskin (Ed.), *Youth Gangs and Community Intervention: Research, Practice, and Evidence* (pp.109-126). New York, NY: Columbia University Press.

Daggett, L. R., & Rolde, E. J. (1980). Decriminalization of drunkenness: Effects on the work of suburban police. *Journal of Studies on Alcohol*, *41*(9), 819-828.

Decker, S. H., Pyrooz, D. C., Sweeten, G., & Moule, R. K. (2014). Validating self-nomination in gang research: Assessing differences in gang embeddedness across non-, current, and former gang members. *Journal of Quantitative Criminology*, *30*(4), 577-598.

Descormiers, K., & Morselli, C. (2011). Alliances, conflicts, and contradictions in Montreal's street gang landscape. *International Criminal Justice Review*, *21*(3), 297–314.

Dugan, L. (2003). Domestic violence legislation: Exploring its impact on the likelihood of domestic violence, police involvement, and arrest. *Criminology & Public Policy*, *2*(2), 283-312.

Engel, R. S., Sobol, J. J., & Worden, R. E. (2000). Further exploration of the demeanor hypothesis: The interaction effects of suspects' characteristics and demeanor on police behavior. *Justice Quarterly*, *17*(2), 235-258.

Engel, R. S., & Worden, R. E. (2003). Police officers' attitudes, behavior, and supervisory influences: An analysis of problem solving. *Criminology*, *41*(1), 131-166.

Everton, S. F. (2012). *Disrupting dark networks*. New York, NY: Cambridge University Press.

Fagan, J., & Davies, G. (2000). Street stops and broken windows: Terry, race, and disorder in New York City. *Fordham Urban Law Journal*, *28*, 457-504.

Fagan, J., Geller, A., Davies, G., & West, V. (2010). Street stops and broken windows revisited. In S. K. Rice & M. D. White (Eds.). *Race, ethnicity, and policing: New and essential readings* (pp. 309-348). New York, NY: New York University Press.

Finn, M. A., Blackwell, B. S., Stalans, L. J., Studdard, S., & Dugan, L. (2004). Dual arrest decisions in domestic violence cases: The influence of departmental policies. *Crime & Delinquency*, *50*(4), 565-589.

Fleisher, M. S. (2005). Fieldwork research and social network analysis: Different methods creating complementary perspectives. *Journal of Contemporary Criminal Justice*, *21*(2), 120-134.

Fox, A. J. (1972). Outliers in time series. *Journal of the Royal Statistical Society. 34*(3), 350-363.

Freeman, L. C. (2004). The development of social network analysis: A study in the sociology of science. Vancouver: Empirical Press.

Gau, J. M., & Brunson, R. K. (2010). Procedural justice and order maintenance policing: A study of inner-city young men's perceptions of police legitimacy. *Justice Quarterly*, *27*(2), 255-279.

Geller, A., & Fagan, J. (2010). Pot as pretext: Marijuana, race, and the new disorder in New York City street policing. *Journal of Empirical Legal Studies*, *7*(4), 591-633.

Gelman, A., Fagan, J., & Kiss, A. (2007). An analysis of the New York City police department's "stop-and-frisk" policy in the context of claims of racial bias. *Journal of the American Statistical Association*, *102*(479), 813-823.

Granovetter, M. (1985). Economic action and social structure: The problem of embeddedness. *American Journal of Sociology*, *91*(3), 481-510.

Gravel, J. (2013). *Jack-of-all-trades: Social capital, criminal versatility, and brokerage in a street gang network.* Masters thesis, Simon Fraser University.

Gravel, J., Bouchard, M., Descormiers, K., Wong, J. S., & Morselli, C. (2013). Keeping promises: A systematic review and a new classification of gang control strategies. *Journal of Criminal Justice*, *41*(4), 228-242.

Gravel, J., & Tita, G. E. (2015). With great methods come great responsibilities: Social network analysis in the implementation and evaluation of gang programs. *Criminology & Public Policy*, *14*(3), 559-572.

Gravel, J. , & Tita, G. E. (2017). Network perspectives of crime. In *Oxford Research Encyclopedia of Criminology and Criminal Justice*. Retrieved from http://criminology.oxfordre.com/view/10.1093/acrefore/9780190264079.001.0001/acrefore-9780190264079-e-251.

Green, B., Horel, T., & Papachristos, A. V. (2017). Modeling contagion through social networks to explain and predict gunshot violence in Chicago, 2006 to 2014. *JAMA Internal Medicine*, *177*(3), 326-333.

Grogger, J. (2002). The effects of civil gang injunctions on reported violent crime: Evidence from Los Angeles County. *The Journal of Law and Economics*, *45*(1), 69-90.

Hagan, J. (1993). The social embeddedness of crime and unemployment. *Criminology*, *31*(4), 465-491.

Harcourt, B. E. (2008). *Against prediction: Profiling, policing, and punishing in an actuarial age*. Chicago, IL: The University of Chicago Press.

Harris, K. M., Halpern, C. T., Whitsel, E., Hussey, J., Tabor, J., Entzel, P., & Udry, J. R. (2009). *The national longitudinal study of adolescent health: Research design*. Chapel Hill, NC: Carolina Population Center, University of North Carolina-Chapel Hill.

Haubert, D. P. (2011, September 16). Early release of felons will challenge public safety. *Long Beach Press-Telegram*, p.15A.

Haynie, D. L. (2001). Delinquent peers revisited: Does network structure matter? *American Journal of Sociology*, *106*(4), 1013-1057.

Hennigan, K. M., & Sloane, D. (2013). Improving civil gang injunctions. *Criminology & Public Policy*, *12*(1), 7-41.

Hirschel, D., Buzawa, E., Pattavina, A., & Faggiani, D. (2007). Domestic violence and mandatory arrest laws: To what extent do they influence police arrest decisions? *Journal of Criminal Law and Criminology*, *98*(1), 255-298.

Hughes, L. A., & Short, J. F. (2005). Disputes involving youth street gang members: Micro-social contexts. *Criminology*, *43*(1), 43-76.

Hyndman, R. J., & Khandakar, Y. (2008). Automatic time series forecasting: The forecast package for R. *Journal of Statistical Software*, *26*(3), 1-22.

Hyndman, R. J., O'Hara-Wild, M., Bergmeir, C., Razbash, S., & Wang, E. (2017). Forecast: Forecasting functions for time series and linear models, R package version 8.1. Retrieved from http://github.com/robjhyndman/forecast.

Jenkins, M. J. (2016). Police support for community problem-solving and broken windows policing. *American Journal of Criminal Justice*, *41*(2), 220-235.

Kennedy, D. M., Braga, A. A., & Piehl, A. M. (1997). The (un) known universe: Mapping gangs and gang violence in Boston. In D. L. Weisburd and T. McEwen (Eds.), *Crime mapping and crime prevention* (pp.219-262). New York, NY: Criminal Justice Press.

Klein, M. W. (1971). *Street gangs and street workers*. Englewood Cliffs, NJ: Prentice-Hall.

Klein, M. W., & Crawford, L. Y. (1967). Groups, gangs, and cohesiveness. *Journal of Research in Crime and Delinquency*, *4*(1), 63-75.

Klein, M. W., & Maxson, C. L. (2006). *Street gang patterns and policies*. New York, NY: Oxford University Press.

Klinger, D. A. (2004). Environment and organization: Reviving a perspective on the police. *The Annals of the American Academy of Political and Social Science*, *593*(1), 119-136.

Knecht, A., Snijders, T. A., Baerveldt, C., Steglich, C. E., & Raub, W. (2010). Friendship and delinquency: Selection and influence processes in early adolescence. *Social Development*, *19*(3), 494-514.

Kreager, D. A., Schaefer, D. R., Bouchard, M., Haynie, D. L., Wakefield, S., Young, J., & Zajac, G. (2016). Toward a criminology of inmate networks. *Justice Quarterly*, *33*(6), 1000-1028.

Kreager, D. A., Young, J. T., Haynie, D. L., Bouchard, M., Schaefer, D. R., & Zajac, G. (2017). Where "old heads" prevail: Inmate hierarchy in a men's prison unit. *American Sociological Review*, *82*(4), 685-718.

Krebs, V. E. (2002). Mapping networks of terrorist cells. *Connections*, *24*(3), 43-52.

Kreit, A. (2016). Marijuana legalization and pretextual stops. *UC Davis Law Review*, *50*(2), 741-772.

Krohn, M. D. (1986). The web of conformity: A network approach to the explanation of delinquent behavior. *Social Problems*, *33*(6), s81-s93.

Kubrin, C. E. (2008). Making order of disorder: A call for conceptual clarity. *Criminology & Public Policy*, *7*(2), 203-213.

Kubrin, C., & Seron, C. (2016). The prospects and perils of ending mass incarceration in the United States. The Annals of the American Academy of Political and Social Science, *664*(1), 16-24.

Latapy, M., Magnien, C., & Del Vecchio, N. (2008). Basic notions for the analysis of large two-mode networks. *Social Networks*, *30*(1), 31-48.

Levitt, S. D. (1998). The relationship between crime reporting and police: Implications for the use of Uniform Crime Reports. *Journal of Quantitative Criminology*, *14*(1), 61-81.

López-de-Lacalle, J. (2017). tsoutliers: Detection of Outliers in Time Series. R package version 0.6-6. https://CRAN.R-project.org/package=tsoutliers

Los Angeles City Attorney (n.d.). List of gang injunctions. Retrieved from https://www.lacityattorney.org/gang-injunction.

Lundman, R. J. (1994). Demeanor or crime? The midwest city police-citizen encounters study. *Criminology*, *32*(4), 631-656.

Maloff, D. (1981). A review of the effects of the decriminalization of marijuana. *Contemporary Drug Problems*, *10*(3), 307-322.

Manzer, T. (2011, September, 25). 'Everybody's problem'. *Long Beach Press-Telegram*, p.1A.

Mastrofski, S. D. (2004). Controlling street-level police discretion. *The Annals of the American Academy of Political and Social Science*, *593*(1), 100-118.

Mastrofski, S. D., Worden, R. E., & Snipes, J. B. (1995). Law enforcement in a time of community policing. *Criminology*, *33*(4), 539-563.

Maxson, C. L. (2004). Civil gang injunctions: The ambiguous case of the national migration of a gang enforcement strategy. In F.-A. Esbensen, S. G. Tibbetts, & L. Gaines (Eds.), *American youth gangs at the millennium* (pp.375-389). Long Grove, IL: Waveland Press.

Maxson, C. L., Hennigan, K. M., & Sloane, D. C. (2005). "It's getting crazy out there": Can a civil gang injunction change a community?. *Criminology & Public Policy*, *4*(3), 577-605.

McCleary, R., McDowall, D., & Bartos, B. J. (2017). *Design and analysis of time series experiments*. New York, NY: Oxford University Press.

McDonnell, J. (2014). Innovative injunctions wrest Long Beach streets from gang's grip. *Police Magazine*, March 2014, Retrieved from http://www.policechiefmagazine.org/innovative-injunctions-wrest-long-beach-streets-from-gangs-grip/

McDonnell, J., & Wacker, C. (2012). Long Beach PD effectively uses Laserfiche: Modern technology fighting a 50-year gang problem. Retrieved from https://www.hendonpub.com/law_and_order/articles/2012/10/long_beach_pd_effectively_uses_laserfiche.

McGloin, J. M. (2005). Policy and intervention considerations of a network analysis of street gangs. *Criminology & Public Policy*, *4*(3), 607-635.

McGloin, J. M., & Kirk, D. S. (2010). An overview of social network analysis. *Journal of Criminal Justice Education*, *21*(2), 169–181.

McGloin, J. M., & Nguyen, H. (2014). The importance of studying co-offending networks for criminological theory and policy. In C. Morselli (Ed.), *Crime and networks* (pp.13-27). New York, NY: Routledge.

McGloin, J. M., Sullivan, C. J., Piquero, A. R., & Bacon, S. (2008). Investigating the stability of co-offending and co-offenders among a sample of youthful offenders. *Criminology*, *46*(1), 155-188.

Meares, T. (2015). Broken windows, neighborhoods, and the legitimacy of law enforcement or why I fell in and out of love with Zimbardo. *Journal of Research in Crime and Delinquency*, *52*(4), 609-625.

Mignon, S. I., & Holmes, W. M. (1995). Police response to mandatory arrest laws. *Crime & Delinquency*, *41*(4), 430-442.

Miller, W. B. (1958). Lower class culture as a generating milieu of gang delinquency. *Journal of Social Issues*, *14*(3), 5-19.

Mitchell, J. C. (1969). The concept and use of social networks. In J. C. Mitchell (Ed.), *Social networks in urban situations: Analyses of personal relationships in Central African towns* (pp. 1-44). Manchester, UK: Manchester University Press.

Morselli, C. (2003). Career opportunities and network-based privileges in the Cosa Nostra. *Crime, Law and Social Change*, *39*(4), 383-418.

Morselli, C. (2009). *Inside Criminal Networks*. New York, NY: Springer.

Morselli, C. (2014). Introduction. In C. Morselli (Ed.), *Crime and networks* (pp.1-9). New York, NY: Routledge.

Muftić, L. R., Bouffard, J. A., & Bouffard, L. A. (2007). An exploratory study of women arrested for intimate partner violence: Violent women or violent resistance? *Journal of Interpersonal Violence*, *22*(6), 753-774.

Muniz, A. (2014). Maintaining racial boundaries: Criminalization, neighborhood context, and the origins of gang injunctions. *Social Problems*, *61*(2), 216-236.

Myers, T. A. (2009). The unconstitutionality, ineffectiveness, and alternatives of gang injunctions. *Michigan Journal of Race & Law*, *14*(2), 285-305.

Nash, R., Bouchard, M., & Malm, A. (2013). Investing in people: The role of social networks in the diffusion of a large-scale fraud. *Social Networks*, *35*(4), 686-698.

Natapoff, A. (2015). Misdemeanor decriminalization. *Vanderbilt Law Review*, *68*(4), 1055-1116.

Nguyen, H., & Reuter, P. (2012). How risky is marijuana possession? Considering the role of age, race, and gender. *Crime & Delinquency*, *58*(6), 879-910.

O'Deane, M. D. (2012). *Gang injunctions and abatement: Using civil remedies to curb gang-related crimes*. Boca Raton, FL: CRC Press.

O'Deane, M. D., & Morreale, S. A. (2011). Evaluation of the effectiveness of gang injunctions in California. *The Journal of Criminal Justice Research*, *2*(1), 1-32.

Ostrom, E., Parks, R. B., & Whitaker, G. P. (1978). Police agency size: Some evidence on its effects. *Police Studies: International Review of Police Development*, *1*, 34-46.

Ouellet, F., Boivin, R., Leclerc, C., & Morselli, C. (2013). Friends with (out) benefits: co-offending and re-arrest. *Global Crime*, *14*(2-3), 141-154.

Ouellet, M., Bouchard, M., & Charette, Y. (2018). One gang dies, another gains? The network dynamics of criminal group persistence. Manuscript submitted for publication.

Ouellet, M., Bouchard, M., & Hart, M. (2017). Criminal collaboration and risk: The drivers of Al Qaeda's network structure before and after 9/11. *Social Networks*, *51*, 171-177.

Papachristos, A. V. (2009). Murder by Structure: Dominance Relations and the Social Structure of Gang Homicide. *American Journal of Sociology*, *115*(1), 74–128.

Papachristos, A. V. (2011). The coming of a networked criminology. In J. Macdonald (Ed.), *Measuring crime and criminality: Advances in criminological theory* (pp. 101-140). New Brunswick, NJ: Transaction Publishers.

Papachristos, A. V., Braga, A. A., & Hureau, D. M. (2012). Social networks and the risk of gunshot injury. *Journal of Urban Health*, *89*(6), 992-1003.

Papachristos, A. V., Braga, A. A., Piza, E., & Grossman, L. S. (2015). The company you keep? The spillover effects of gang membership on individual gunshot victimization in a co-offending network. *Criminology*, *53*(4), 624-649.

Papachristos, A. V., & Kirk, D. S. (2015). Changing the street dynamic: Evaluating Chicago's group violence reduction strategy. *Criminology & Public Policy*, *14*(3), 525-558.

Papachristos, A. V., & Wildeman, C. (2014). Network exposure and homicide victimization in an African American community. *American Journal of Public Health*, *104*(1), 143-150.

Papachristos, A. V., Wildeman, C., & Roberto, E. (2015). Tragic, but not random: The social contagion of nonfatal gunshot injuries. *Social Science & Medicine*, *125*, 139-150.

People ex. Rel. Gallo v. Acuna, 14 Cal. 4th 1090 (Cal. 1997).

People v. Eastside Longos (2001). Los Angeles County Case No. NC030660 (Cal. Super. Ct. Los Angeles County).
☐
People v. Insane Crips (2003). Los Angeles County Case No. NC033946 (Cal. Super. Ct. Los Angeles County).

People v. Westside Longos (2004). Los Angeles County Case No. NC035222 (Cal. Super. Ct. Los Angeles County).

Petersilia, J., Abarbanel, S., Butler, J., Feldman, M., Hinds, M., Jason, K., ... & Vilkin, C. (2014). *Voices from the field: How California stakeholders view public safety realignment.* Stanford, CA: Stanford Criminal Justice Center.

Petersilia, J., & Snyder, J. (2013). Looking past the hype: 10 questions everyone should ask about California's prison Realignment. *California Journal of Politics and Policy*, *5*(2), 266-306.

Pyrooz, D. C., Sweeten, G., & Piquero, A. R. (2013). Continuity and change in gang membership and gang embeddedness. *Journal of Research in Crime and Delinquency*, *50*(2), 239-271.

Pyrooz, D. C., Turanovic, J. J., Decker, S. H., & Wu, J. (2016). Taking stock of the relationship between gang membership and offending: A meta-analysis. *Criminal Justice and Behavior*, *43*(3), 365-397.

Raab, J., & Milward, H. B. (2003). Dark networks as problems. *Journal of Public Administration Research and Theory*, *13*(4), 413-439.

Rainguet, F. W., & Dodge, M. (2001). The problems of police chiefs: An examination of the issues in tenure and turnover. *Police Quarterly*, *4*(3), 268-288.

Ratcliffe, J. H., Taniguchi, T., Groff, E. R., & Wood, J. D. (2011). The Philadelphia foot patrol experiment: A randomized controlled trial of police patrol effectiveness in violent crime hotspots. *Criminology*, *49*(3), 795-831.

Reiss, A. J. (1988). Co-offending and criminal careers. *Crime and Justice*, *10*, 117-170.

Reiss, A. J., & Farrington, D. P. (1991). Advancing knowledge about co-offending: Results from a prospective longitudinal survey of London males. *Journal of Criminal Law & Criminology*, *82*(2), 360-395.

Roberto, E., Braga, A. A., & Papachristos, A. V. (2018). Closer to guns: The role of street gangs in facilitating access to illegal firearms. *Journal of Urban Health*. Advance online publication. doi: 10.1007/s11524-018-0259-1.

Ross, A., & Walker, A. (2017). The impact of low-priority laws on criminal activity: Evidence from California. *Contemporary Economic Policy*, *35*(2), 239-252.

Russell, W. T. (2003, November 16). Do gang injunctions work? *Long Beach Press-Telegram*, p. A1.

Sampson, R. J., & Groves, W. B. (1989). Community structure and crime: Testing social-disorganization theory. *American Journal of Sociology*, *94*(4), 774-802.

Sarnecki, J. (1986). *Delinquent networks*. Stockholm: National Council for Crime Prevention Sweden.

Sarnecki, J. (1990). Delinquent networks in Sweden. *Journal of Quantitative Criminology*, *6*(1), 31-50.

Sarnecki, J. (2001). *Delinquent networks: Youth co-offending in Stockholm*. New York, NY: Cambridge University Press.

Saunders, D. G. (1995). The tendency to arrest victims of domestic violence: A preliminary analysis of officer characteristics. *Journal of Interpersonal Violence*, *10*(2), 147-158.

Schaefer, D. R. (2012). Youth co-offending networks: An investigation of social and spatial effects. *Social Networks*, *34*(1), 141-149.

Schaefer, D. R., Bouchard, M., Young, J. T., & Kreager, D. A. (2017). Friends in locked places: An investigation of prison inmate network structure. *Social Networks*, *51*, 88-103.

Schaefer, D. R., Rodriguez, N., & Decker, S. H. (2014). The role of neighborhood context in youth co-offending. *Criminology*, *52*(1), 117-139.

Sellin, T. (1931). The basis of a crime index. *Journal of the American Institute of Criminal Law & Criminology*, *22*(3), 335-356.

Sherman, L. W. (2018). Policing domestic violence 1967–2017. *Criminology & Public Policy*, *17*(2), 453-465.

Sherman, L. W., Schmidt, J. D., Rogan, D. P., Gartin, P. R., Cohn, E. G., Collins, D. J., & Bacich, A. R. (1991). From initial deterrence to long-term escalation: Short-custody arrest for poverty ghetto domestic violence. *Criminology*, *29*(4), 821-850.

Short, J. F. (2009). Gangs, law enforcement, and the academy. *Criminology & Public Policy*, *8*(4), 723-731.

Short, J. F. & Strodtbeck, F. (1965). *Group process and gang delinquency.* Chicago, IL: The University of Chicago Press.

Sierra-Arevalo, M., Charette, Y., & Papachristos, A. V. (2017). Evaluating the effect of project longevity on group-involved shootings and homicides in New Haven, Connecticut. *Crime & Delinquency*, *63*(4), 446-467.

Sierra-Arévalo, M., & Papachristos, A. V. (2017). Social networks and gang violence reduction. *Annual Review of Law and Social Science*, *13*, 373-393.

Single, E. W. (1989). The impact of marijuana decriminalization: an update. *Journal of Public Health Policy*, *10*(4), 456-466.

Skolnick, J. H. (1966). *Justice without trial: Law enforcement in a democratic society*. New York, NY: John Wiley & Sons.

Smith, S. (2000). Civil banishment of gang members: Circumventing criminal due process requirements? *University of Chicago Law Review*, *67*(4), 1461-1487.

Smith, C. M., & Papachristos, A. V. (2016). Trust thy crooked neighbor: multiplexity in Chicago organized crime networks. *American Sociological Review, 81*(4), 644-667.

Smithson, H., & Ralphs, R. (2016). Youth in the UK: 99 problems but the gang ain't one? *Safer Communities*, *15*(1), 11-23.

Sousa, W. H. (2010). Paying attention to minor offenses: Order maintenance policing in practice. *Police Practice and Research: An International Journal*, *11*(1), 45-59.

Sousa, W. H., & Kelling, G. L. (2010). Police and the reclamation of public places: a study of MacArthur Park in Los Angeles. *International Journal of Police Science & Management*, *12*(1), 41-54.

Sparrow, M. K. (1991). The application of network analysis to criminal intelligence: An assessment of the prospects. *Social networks*, *13*(3), 251-274.

Stewart, G. (1998). Black codes and broken windows: The legacy of racial hegemony in anti-gang civil injunctions. *The Yale Law Journal*, *107*(7), 2249-2279.

Stolzenberg, L., & D'Alessio, S. J. (2008). Co-offending and the age-crime curve. *Journal of Research in Crime and Delinquency*, *45*(1), 65-86.

Stuart, F. (2016). *Down, out, and under arrest: Policing and everyday life in skid row*. Chicago, IL: The University of Chicago Press.

Suggs, D. L. (1981). A qualitative and quantitative analysis of the impact of Nebraska's decriminalization of marijuana. *Law and Human Behavior*, *5*(1), 45-71.

Sutherland, E. H. (1939). *Principles of criminology*. New York, NY: J. B. Lippincott.

Suttles, G. D. (1968). *The social order of the slum*. Chicago, IL: The University of Chicago Press.

Tapia, M. (2011). Gang membership and race as risk factors for juvenile arrest. *Journal of Research in Crime and Delinquency*, *48*(3), 364-395.

Taylor, R. B. (2001). *Breaking away from broken windows: Baltimore neighborhoods and the nationwide fight against crime, grime, fear, and decline*. Boulder, CO: Westview Press.

Thornberry, T. P., Krohn, M. D., Lizotte, A. J., Smith, C. A., & Tobin, K. (2003). *Gangs and delinquency in developmental perspective*. New York, NY: Cambridge University Press.

Thrasher, F. M. (1927). *The gang: A study of 1,313 gangs in Chicago*. Chicago, IL: The University of Chicago Press.

Tita, G. E., & Boessen, A. (2011). Social networks and the ecology of crime: Using social network data to understand the spatial distribution of crime. In D. Gadd, S. Karstedt, & S. F. Messner (Eds.), *The SAGE handbook of criminological research methods* (pp. 128–142). Thousand Oaks, CA: SAGE Publishing.

Tita, G. E., & Radil, S. M. (2011). Spatializing the social networks of gangs to explore patterns of violence. *Journal of Quantitative Criminology*, *27*(4), 521–545.

Tita, G. E., Riley, K. J., Ridgeway, G., Grammich, C., Abrahamse, A. F., & Greenwood, P. W. (2003). *Reducing gun violence in East Los Angeles: Results from an intervention in East Los Angeles*. Santa Monica, CA: RAND Corporation.

Tracy, M., Braga, A. A., & Papachristos, A. V. (2016). The transmission of gun and other weapon-involved violence within social networks. *Epidemiologic Reviews*, *38*(1), 70-86.

Tremblay, P. (1993). Searching for suitable co-offenders. In R. V. Clarke & M. Felson (Eds.), *Routine activity and rational choice* (pp. 17–36). New Brunswick, NJ: Transactions Publishers.

Tremblay, P., Charest, M., Charette, Y., & Tremblay-Faulkner, M. (2016). Le délinquant affilié: La sous-culture des gangs de rue haïtiens de Montréal. Montreal: Liber. [The connected delinquent: Montreal's Haitian street gang subculture].

Tsay, R. S. (1988). Outliers, level shifts, and variance changes in time series. *Journal of Forecasting*, *7*(1), 1-20.

Tyler, T. R., Fagan, J., & Geller, A. (2014). Street stops and police legitimacy: Teachable moments in young urban men's legal socialization. *Journal of Empirical Legal Studies*, *11*(4), 751-785.

Valasik, M. A. (2014). *"Saving the world, one neighborhood at a time": The role of civil gang injunctions at influencing gang behavior*. Doctoral Dissertation, University of California, Irvine.

Warr, M. (2002). *Companions in crime: The social aspects of criminal conduct*. New York, NY: Cambridge University Press.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*. New York, NY: Cambridge University Press.

Weerman, F. M. (2003). Co-offending as social exchange: Explaining characteristics of co-offending. *British Journal of Criminology*, *43*(2), 398-416.

Weerman, F. M. (2011). Delinquent peers in context: A longitudinal network analysis of selection and influence effects. *Criminology*, *49*(1), 253-286.

Weerman, F. M., Wilcox, P., & Sullivan, C. J. (2018). The short-term dynamics of peers and delinquent behavior: An analysis of bi-weekly changes within a high school student network. *Journal of Quantitative Criminology*, *34*(2), 431-463.

Weisburd, D., & Eck, J. E. (2004). What can police do to reduce crime, disorder, and fear?. *The Annals of the American Academy of Political and Social Science*, *593*(1), 42-65.

Weiss, C. H. (1995). Nothing as practical as good theory: Exploring theory-based evaluation for comprehensive community initiatives for children and families. In J. I. Connell, A. C. Kubish, L. B. Schorr, and C. H. Weiss (Eds.), *New approaches to evaluating community initiatives: Concepts, methods, and contexts* (pp. 65-92). Washington, DC: The Aspen Institute.

Welsh, B. C., Braga, A. A., & Bruinsma, G. J. (2015). Reimagining broken windows: From theory to policy. *Journal of Research in Crime and Delinquency*, *52*(4), 447-463.

Wilson, J. Q. (1968). *Varieties of police behavior: The management of law and order in eight communities.* Cambridge, MA: Harvard University Press.

Wilson, J. Q., & Kelling, G. L. (1982). Broken windows. *Atlantic Monthly*, *249*(3), 29-38.

Worden, R. E., & Shepard, R. L. (1996). Demeanor, crime, and police behavior: A reexamination of the police services study data. *Criminology*, *34*(1), 83-105.

Zimring, F. E. & Hawkins, G. J. (1973). *Deterrence: The legal threat in crime control.* Chicago, IL: The University of Chicago Press.