Studying Accomplice Selection and Criminal Specialisation Through Networks

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A thesis presented for the degree of Doctor of Philosophy

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Declaration

I, Alberto Nieto Tibaquirá, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Acknowledgement

I want to express my deepest gratitude to my wife, Mariana Gamba, for her unwavering support and encouragement throughout the entire process of writing this thesis. Mariana, thank you for always being there for me and helping me stay motivated. Emilia, my three-year-old daughter, was born during the second year of my programme. Her arrival in my life provided a strong motivation to finish this thesis. Emilia: thank you for being an inspiration and showing me the way. My son, Lorenzo, came into our lives in the final stretch of the doctorate, giving it the last push needed to finish the thesis. Son, this thesis is also dedicated to you. I also want to thank my parents, Carlos and Martha, and my brother, Carlos, for their love and support, which helped me start a new life in the UK.

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   Publication 2 in Chapter 6

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Supervisors:

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Abstract

Understanding cooperation between offenders is essential for understanding criminality. It occurs across a broad range of criminal behaviours - it can be seen between a pair of shoplifters or in complex transnational criminal organisations - and can have significant implications for whether and how crimes are committed. Crime researchers have studied different aspects of *co-offending* - the term used to describe instances where multiple individuals collaborate to commit a crime - across a range of settings. In particular, some theories have been proposed to understand why people decide to co-offend and how they select their accomplices. Having a better understanding of how offenders go about selecting accomplices can support Law Enforcement Agencies (LEAs) in identifying ways to reduce crime by, for example, preventing motivated offenders from finding suitable partners.

There have been limited attempts to refine or falsify existing theories by examining data on a large scale. This thesis endeavours to address this gap by adopting a network approach, whereby co-offending behaviours are examined through the analysis of connections between offenders. Employing a network approach can unveil concealed patterns and structures that may not be readily apparent when studying co-offenders or criminal events in isolation. This approach possesses the capability to capture intricate relationships, reveal obscured patterns, and employ network science concepts, rendering it a valuable

instrument in advancing the understanding of criminal collaboration.

In particular, it employs a range of analytical strategies to explore a number of aspects of the accomplice selection process. By examining networks modelling the interactions between offenders and criminal events, it investigates the extent to which offenders procure accomplices from their former associates. It also examines the evolution of co-offending networks (i.e., networks connecting co-offenders) to identify the underlying mechanisms that might explain how new co-offending relationships are created. Additionally, this thesis explores the criminal specialisation of adult co-offending groups, an issue that has not been fully addressed in the literature.

The studies included in this thesis were completed using a unique dataset of information on adult offenders ($N = 274,689$) linked to criminal investigations ($N = 286,591$) in Bogotá, Colombia. The data provided by the Attorney General's Office (AGO) was not restricted to a specific set of offences; hence, it comprises all possible crime types that were investigated and prosecuted in this city between 2005 and 2018. The records contain details of arrestees, defendants on trial, and convicted defendants. While the use of arrest records and court files in co-offending studies is commonplace, it is infrequent to find both sources of information combined in one comprehensive data set.

The results suggest that co-offending networks, like other social networks, exhibit some degree of *triadic closure*. Given the connections $A - B$ (i.e., A co-offends with B) and $A - C$, it is likely to see a connection of the sort $B - C$. This finding suggests that associates might play a crucial role in procuring new accomplices for their former accomplices. Moreover, this thesis shows how the evolution of co-offending networks can be studied by integrating multiple mechanisms that describe how social networks grow. Specifically, it shows that popular offenders (i.e., those with numerous connections to other offenders) might not explain how co-offending networks evolve. It also shows that some offenders do not limit co-offending relationships to single events, as previous studies have shown. On the contrary, re-using accomplices was favoured over finding new partners (e.g., events of the sort $A \rightarrow B$ - or 'A co-offends with B' - are followed by similar events $A \rightarrow B$). The results also support the hypothesis that offenders change roles throughout their criminal careers. They go from followers to recruiters (or vice versa), allowing co-offending networks to grow by reciprocating co-offending relationships (e.g., events similar to $A \rightarrow B$ are followed by instances of the sort $B \rightarrow A$). This thesis also shows that criminal specialisation is a characteristic observed among co-offending groups. Nearly half of those groups that re-offended exhibited traits of becoming specialists in particular types of crimes, such as those affecting private property.

The thesis contributes to the literature on co-offending by examining the behaviours exhibited by co-offending networks, challenging findings from previous studies, and providing inputs for disrupting co-offending relationships. It also contributes to networked criminology - an emerging field that combines network science and crime-related theories - by showing how networks can be used to study accomplice selection and identify co-offending groups. A number of methodological issues are also discussed in this thesis, including why co-offending studies need to use bipartite networks to gain a better understanding of criminal collaboration, the advantages of using null models for assessing the statistical significance of network statistics, and how co-offending network evolution can be analysed as the result of discrete choices made by co-offenders.

Impact Statement

The potential impact of this thesis goes far beyond academia. In addition to providing valuable insights into the dynamics of co-offending networks, the research findings offer practical applications for law enforcement agencies (LEAs). For example, the thesis sheds light on the mechanisms underlying accomplice selection and the evolution of co-offending networks. LEAs can leverage this knowledge to improve their strategies in combating criminal activities. By understanding how offenders procure accomplices from their former associates, targeted interventions to disrupt criminal networks can be developed. These strategies could include monitoring known associates of high-risk offenders or implementing preventive measures to limit the spread of co-offending relationships.

Crime reduction strategies can also be developed based on the findings presented in this study. Offender collaboration can be minimised by understanding the preference for reusing accomplices over finding new partners. Focusing on breaking these reoccurring partnerships can make it harder for criminals to plan and execute complex criminal activities. Implementing such strategies could decrease the overall crime rate and make illegal operations more difficult to sustain.

The insights gained from studying criminal specialisation within co-offending groups can guide the formulation of more effective criminal justice policies. Understanding which co-offending groups specialise in specific crimes can help policymakers allocate resources more efficiently. Tailored interventions for particular crime types can improve crime prevention and public safety.

An essential aspect of this thesis is its focus on studying co-offending in Colombia, a setting that has been understudied in the context of criminal collaboration. By exploring co-offending behaviours in this unique context, the research contributes to a deeper understanding of criminal dynamics in a region where crime patterns and social structures may differ significantly from more extensively researched countries (e.g., Canada, Sweden, the USA, and the UK). The insights gained from this study are particularly valuable for law enforcement agencies and policymakers in Colombia, as they can inform targeted strategies to combat crime effectively.

From an academic perspective, this thesis contributes to the emerging field of networked criminology, which combines network science and crime-related theories to study deviant behaviour. This interdisciplinary approach opens new avenues for future research in understanding criminality and cooperation patterns. By highlighting how a networked approach can provide more insights into crime-related activities, the thesis encourages further exploration into applying network analysis techniques in criminological studies.

The methodological approaches used in this study uncover deficiencies in prior research while also providing novel insights previously unexplored in this field. For instance, it elucidates how specific studies introduced bias when assessing the degree of transitivity in co-offending relationships. Furthermore, this thesis employs a novel technique grounded in network science that conceives the evolution of co-offending networks as a series of discrete decisions taken by offenders when selecting their accomplices. Moreover, the thesis relies on null models to assess the statistical significance of various network metrics, a procedure rarely observed within the domain of networked criminology.

In conclusion, this thesis holds promise for making valuable contributions to understanding criminal cooperation. Practitioners and researchers can benefit from the findings and methodological advancements presented here. This research can foster positive impacts on crime reduction, criminal justice policies, and the development of networked criminology as a discipline. Moreover, the knowledge generated from this thesis can help build safer and more secure communities by tackling criminal collaboration effectively.

Contents

Chapter 1

Introduction

1.1 Background, Research Questions, and Contributions

Like in other walks of life, collaboration is a critical ingredient in crime (Bouchard, 2020). Sometimes, two or more individuals must collaborate to successfully execute a crime by completing sequential or parallel tasks or combining their skills. Even relatively simple crimes can be committed by various offenders to reduce the likelihood of detection. The term *co-offending* describes those instances in which two or more people collaborate to commit a crime. As far back as 1912, criminologists have studied co-offending. Using court records from Cook County, Illinois (USA), Breckinridge and Abbott (1912) concluded that 'there is scarcely a type of delinquent boy who is not associated with others' (1912, p. 35). Sometime after, another report commented on co-offending prevalence in that same county (Shaw & McKay, 1931). Since these early accounts, criminologists have explored diverse aspects of criminal collaboration. They have reported and theorised about offenders' decisions when selecting accomplices, the traits co-offenders exhibit, and the types of crimes in which they participate. Numerous insights have been gained in this field by observing co-offenders, especially juvenile offenders, in a small set of countries (Australia, Canada, Sweden, the UK, and the USA).

Co-offending was established as a field of study in the 1960s when multiple reports showed that collaboration was crucial to understanding criminality, especially among juveniles (Carrington, 2014). It has expanded in the last two decades thanks to the application of *social network analysis* (Carrington, 2011). Some have anticipated that it would become increasingly challenging to analyse co-offending without considering the overall social structure in which co-offender interactions occur (Bouchard & Amirault, 2013). Social network analysis (SNA) comprises theories and tools to study human interactions, including those derived from crime-related activities (e.g., who co-offended with whom). Networks are at the core of SNA. These mathematical objects are comprised of nodes and edges (also referred to as links) that model how entities in a system are connected (Newman, 2018). Nodes can represent entities such as offenders, locations, or criminal events. At the same time, the edges convey information about the connections between these entities (e.g., which set offenders participated in a particular criminal event or which offenders tend to commit their crimes in specific locations). Edges can also convey information about the intensity of connections by adding a *weight*. For example, in a network in which offenders (nodes) are connected by the crimes they have co-executed, a pair of co-offenders that have committed multiple crimes would be represented with a *heavier* link, compared to a pair that only committed one crime. Networks provide information about the system as a whole, a subset of nodes or single nodes. The study of crime-related networks has benefited from advancements in *network science* (Bouchard & Malm, 2016). In this multidisciplinary field, computer scientists, mathematicians, physicists, and sociologists, among others, have contributed significantly to a better understanding of the dynamics displayed by networks (Barabási, 2016).

Network science's progress has helped researchers understand criminal collaboration by revisiting old research questions and raising new ones. This thesis uses new analytical tools and formal methods to understand accomplice selection and criminal specialisation of co-offending groups. As explained in Chapter 2, there have been few attempts to examine accomplice selection theories from a networked perspective (see also Bouchard & Malm, 2016). SNA's logic of mapping and studying connections between entities makes it a suitable tool for examining co-offender relationships and the behaviour of the large, complex networks that emerge when numerous co-offenders and criminal events are considered. It is possible to examine accomplice selection theories by comparing and contrasting them with the mechanisms that describe how new connections are created in networks. This is the underlying approach used in the studies included in Chapters 5 and 6. Network science tools can also facilitate the identification of meaningful sub-structures in large co-offending networks (i.e., proxies of co-offending groups) and the crimes that bound offenders together. This information can shed light on the extent to which co-offenders specialise in certain crimes, a research area not fully explored in the literature (see Chapter 7).

Accordingly, **this thesis aims to answer two broad questions**:

- What insights can we gather about the process of choosing accomplices based on the dynamics of co-offending networks?

- After adult co-offenders have chosen their partners in crime, do they typically focus on particular categories of offences?

The motivations behind these questions are five-fold. First, crime can be prevented when motivated offenders cannot find suitable accomplices (Felson, 2003). Hence, by focusing on accomplice selection, this thesis aims to understand this process better and develop new insights that could help prevent crime. For example, these insights can be used to identify ways to disrupt the accomplice selection process. Second, as explained below, the criminal specialisation of co-offending groups has not been explored in the literature. Analysing the crimes committed by co-offending groups can provide additional evidence to inform policy decisions (e.g., by facilitating the identification of groups that have specialised in crimes that cause the most significant amount of harm). As explained in the next Chapter, criminological research on co-offending has mainly focused on exploring the traits of juvenile offenders. Hence, the third motivation behind this work was to examine how adult co-offenders select their accomplices from a network perspective (although no comparisons between adult and juvenile offenders are examined here). Fourth, Colombian law enforcement agencies (LEA), such as the AGO, have collected much crime-related data. Still, there have been few attempts to use networks to analyse this data and extract meaningful insights to prevent crime. The author spent four years as a senior policy advisor at the AGO. During his tenure, he saw first-hand the lack of network-related research initiatives to exploit information gathered through criminal investigations to study co-offending. Accordingly, this thesis shows how to use a networked approach to analyse existing crime-related data held by LEAs, inside and outside Colombia, to produce findings that could guide interventions aimed at reducing crime.

McGloin and Nguyen (2013) contended that policymakers tend to ignore the fact that people commit crimes in groups when designing interventions to reduce, prevent, or punish criminal behaviour. Accordingly, the fifth motivation behind these research questions is to explore potential ways to prevent or reduce crime by better understanding accomplice selection processes. Therefore, this thesis aligns with *crime science's* rationale (Laycock, 2013) by showing how network science can inform crime prevention efforts. The work presented here does not include a detailed list of crime prevention strategies; however, it demonstrates that it is necessary to consider that adult co-offenders commit crimes, and some of them specialise in crimes that harm society. It also outlines findings and suggests analytical approaches that practitioners and crime researchers might find helpful when designing interventions to prevent crime.

By combining network science and crime-related theories, this thesis aligns with networked criminology's approach to studying crime (Papachristos, 2011). Thus, the studies presented here contribute to this interdisciplinary field that uses a network approach in tandem with criminological theories to study crime events. In particular, this thesis further develops Bichler (2019)'s 'theory of networked opportunity', as it tries to understand how social networks shape the interactions between offenders and their surroundings conducive to opportunities for crime. A testable rule of this theory (Rule No. 6) posits that information and resources available to individuals through their social networks (direct and indirect contacts) affect their perceptions and decisions to engage in criminal activity (Bichler, 2019). This thesis examines this rule by empirically studying accomplice selection from a network perspective.

The setting of this thesis is Colombia's capital, Bogotá, a city with multiple security challenges. These challenges stem from the massive migration of internally displaced people in the last decade. According to the Internal Displacement Monitoring Centre, Colombia has nearly five million internally displaced people triggered by violence in rural areas that have arrived in major cities, including Bogotá (Internal Displacement Monitoring Centre, 2023). This Centre has found that internally displaced people, especially the young, are at a higher risk of being recruited by criminal groups (Internal Displacement Monitoring Centre, 2021). Accordingly, this situation supposes, in principle, that more people might participate in group crime in this city than in cities located in countries without internal displacement. This violence has turned Colombia into a country with one of the highest homicide rates in the region. The statistics collected by the United Nations Office on Drugs and Crime (UNODC, 2023) show that Colombia had, on average, 30.3 intentional homicides per 100K people, per year, between 2010 and 2018. In this same time window, neighbouring countries had 11.2.[1] As a comparison, the UK had, on average, 1.06 intentional homicides per 100K people per year during the same period. Competition between criminal groups to control illicit drug markets can partly explain this deadly violence (Felbab-Brown, 2009), and Bogotá has become a sought-after city for criminal groups. Recent journalistic accounts suggest that the violence triggered by the competition between criminal groups - including those from the neighbouring country, Venezuela - has become an additional security challenge in this city (e.g., Insight Crime, 2022). Testing whether these conditions (i.e., internal displacement, illicit drug trafficking,

[1]Neighbouring countries include Argentina, Bolivia, Brazil, Ecuador, Chile, Ecuador, Paraguay, Peru, Uruguay, and Venezuela.

and violence) cause more co-offending sits outside the scope of this thesis. Still, they reveal the relevance of studying co-offending outside the small set of countries from which the majority of evidence about co-offending comes.

The studies included in this thesis relied on a unique data set containing information about criminal investigations conducted by the Attorney General's Office (AGO) of co-offenders ($\geq$ 18 years) involved in illegal activities. The data set included information about offenders ($N = 274,689$) linked to criminal investigations ($N = 286,591$) in Colombia's capital, Bogotá, between 2005 and 2018. No specific criteria for including crime types were used here; hence, all possible crimes in Colombia's Criminal Law were included. Chapter 4 presents more details about this data set and some descriptive statistics.

1.2 Contributions

The contributions of this thesis are eight-fold. Three of them correspond to the substantive findings of each study, and five to overarching methodological contributions.

Substantive findings

1. This thesis shows that co-offending networks, like other social networks, exhibit some triadic closure. This trait implies that two offenders are more likely to commit crimes together if they share an accomplice. Accordingly, LEAs should note co-offending networks' role in co-offending - specifically in sourcing potential accomplices - to aim interventions at disrupting the accomplice selection process.

2. It shows that the behaviours displayed by co-offending networks

could be described using insights about growth mechanisms used to examine social networks in general. Specifically, it suggests that co-offending networks evolve differently through a combination of principles driving relationship formation in co-offending - which correspond to accomplice selection theories. If the evolution of co-offending networks can be described through multiple mechanisms, then disruptive interventions should be tailored according to the behaviours displayed by each network.

3. This thesis reveals that some co-offending groups tend toward criminal specialisation. Almost half of those who re-offended demonstrated traits of specialising in crimes affecting private property. Information about criminal specialisation in co-offending groups, combined with tools to measure harm caused by certain crime types, can provide policy-relevant insights to direct resources towards disrupting those groups that can potentially cause more harm to society.

Methodological contributions

4. It measures triadic closure in co-offending networks by estimating this trait in networks modelling offenders' interactions with criminal events (i.e., bipartite networks), avoiding a bias introduced in past studies assessing transitivity in co-offending relationships using one-mode networks (i.e., those showing connections between offenders and not between offenders and criminal events).

5. It shows how null models can be used to assess the statistical significance of network statistics. This approach is commonly employed in other fields that use networks to study patterns

of connections but is not yet widely implemented in networked criminology.

6. It relies on a recently-developed approach in network science that considers the evolution of networks as the result of discrete decisions made by offenders when selecting new accomplices. Combined with simulations analyses, it was possible to elucidate the network growth mechanisms that can describe the behaviours displayed by co-offending networks.

7. It expands upon the typical one-mode networks used in networked criminology by using bipartite networks to analyse the interactions between offenders and events. By using bipartite networks, it is possible to get more information about the patterns of interactions seen between the entities under study. This information is generally lost when transforming bipartite networks into one-mode networks (a common approach in networked criminology).

8. As with other social networks, co-offending networks tend to change over time. Accordingly, time was incorporated as a variable into the analysis of dynamic co-offending networks, which goes beyond the usual approach in networked criminology of studying static criminal networks.

Overall, this thesis aims to advance the co-offending and networked criminology fields by analysing the creation of new connections in co-offending networks and comparing these behaviours to existing theories about accomplice selection (primarily through Contributions 1 and 2). Accordingly, this thesis resonates with Weerman (2014)'s critiques about the wealth of empirical research on co-offending and the few theoretical contributions that explain why people co-offend and how they choose their accomplices. Moreover, he criticised the fact that there are few attempts to explicitly test theoretical notions related to the process of co-offending and accomplice selection.

1.3 Structure

Chapter 2 introduces the reader to co-offending research by reviewing the current theories about accomplice selection, the decision to co-offend, and the co-offenders' characteristics. Chapter 3 presents key ideas about network science and argues the advantages of using these tools to study co-offending. Chapter 4 introduces the data used to complete the three studies included here and presents descriptive statistics about the extent of co-offending in Bogotá, Colombia, between 2005 and 2018.

Chapters 5 to 7 contain the three empirical studies through which the previously stated contributions are achieved. Specifically, Chapter 5 discusses the concept of triadic closure in co-offending networks and identifies the similarities between this concept and some elements included in accomplice selection theories (Contribution 1). This Chapter also discusses a methodological approach to avoid introducing a bias in the estimation of clustering coefficients - the statistic used to estimate the presence (or absence) of triadic closure (Contributions 4 and 5). Chapter 6 also looks into the accomplice selection process, but it includes time as a variable and additional mechanisms that describe how networks evolve. Specifically, the study included in this Chapter presents a temporal analysis of three evolving networks and identifies the tools that better represent the behaviours these networks display when growing. As mentioned, most research in networked criminology relies on static networks to learn about the properties of criminal networks. Hence, this study is among those few that exploit temporal information to understand the behaviours displayed by co-offending networks in time (Contributions 2 and 6-8). Turning to the question of criminal specialisation in co-offending groups, Chapter 7 presents an exploratory study that relied on the possibility of extracting meaningful substructures (i.e., bicliques) from large networks to identify co-offending groups and assess their criminal specialisation degree (Contributions 3, 5 and 7). Lastly, Chapter 8 presents a summary of the thesis and a discussion of three unifying themes observed across the chapters: i) the possibility of studying accomplice selection through networks; ii) the insights LEAs might find helpful in preventing crime when adopting a networked approach to study accomplice selection, and iii) the value bipartite networks adds when analysing co-offending relationships.

1.4 Dissemination

Elements of this thesis have been presented at academic conferences (e.g., the 2021 Sunbelt-Network Science Conference) and published in peer-reviewed journals. These publications include:

- Nieto, A., Davies, T., & Borrion, H. (2022). "Offending with the accomplices of my accomplices": Evidence and implications regarding triadic closure in co-offending networks. Social Networks, 70, 325-333.
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- Nieto, A., Davies, T., & Borrion, H. (2023). Examining the importance of existing relationships for co-offending: a temporal

network analysis in Bogotá, Colombia (2005–2018). Applied Network Science, 8(1), 1-31.
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Chapter 2

Academic Literature on Co-offending

2.1 Overview

Criminologists have proposed multiple theories to explain *why* co-offenders decide to co-execute a crime and *how* they select their accomplices. This Chapter reviews these theories and summarises the evidence related to the characteristics displayed by co-offenders, the crime types in which they participate, and the prevalence of co-offending. It also discusses some of the traits displayed by co-offending groups.

The reader will note that the theories and findings presented below mostly relate to research about 'street crime' and juvenile offenders. The disproportionate attention on these crimes and set of offenders suggests a disconnect between co-offending and organised crime studies, even though these two fields of study are interested in crime committed by groups (Felson, 2009). As explained in Chapter 3, this gap is closing as co-offending and organised crime researchers study collaboration in crime-related contexts through a network approach.

2.2 Decision to Co-Offend

Many theoretical perspectives relating to co-offending focus on the decision to collaborate itself - that is, for a given crime, whether to involve a co-offender rather than commit the crime alone. Some of these theoretical perspectives are presented following van Mastrigt (2017)'s classification: co-offending as the result of an instrumental/functional decision, co-offending as an artefact, and co-offending as an event derived from social processes.

Instrumental or functional theories of co-offending regard co-offenders as rational actors, with specific objectives and preferences, who are willing to engage in illegal activities with others based on a deliberate and calculated appraisal of the risks, costs, and benefits (Cornish & Clarke, 2002b). This perspective is closely related to the model of rational economic decision-makers and the rational choice perspective on crime. The former considers individuals as actors seeking to maximise their welfare (Becker, 1993), while the latter regards crime as the result of motivated offenders that have decided to participate in an illegal activity based on a 'conscious thought process' (Clarke & Cornish, 1985, p. 147) bounded by circumstantial factors and the information available at the time of deciding. Following this rationale, co-offending occurs when the perceived benefits of liaising with another person to co-execute a crime exceed the associated risks. These benefits could be in the form of making a crime more profitable or reducing its complexity when executing it. As shown below, co-offending is prevalent in crimes against private property. Those arguing for an instrumental perspective have used this empirical finding as evidence to support their theories since such crimes can benefit from having multiple accomplices performing different roles (e.g., lookouts, drivers, or those providing a hideout after executing the crime) (van Mastrigt, 2017).

Two perspectives of rationality, egocentric and collective, explain why individuals decide to co-offend. The egocentric rationality perspective describes offenders as selfish actors who want to maximise their rewards without considering the rewards or outcomes of their associates. The social exchange theory of co-offending stems from this view of rationality (Weerman, 2003) and tries to explain the decision made by individuals to co-offend and how they select their associates. According to this theory, co-offenders are prepared to exchange material (e.g., a share of the proceeds or payment) and immaterial goods (e.g., information, recognition, or social approval) to access material and immaterial rewards that are more difficult to obtain by solo offending. Following this theory, co-offending might be deemed worthwhile to access material rewards that offenders cannot reach by executing a crime independently (e.g., some crimes might require a division of labour to complete sequential or parallel actions). Similarly, co-offending might help to access immaterial rewards like recognition or acceptance. From this perspective, co-offending is transactional, with the exchange simply being a means for each individual reaching their own goals. Weerman (2003) classified forms of co-offending based on the goods that motivated offenders are willing to exchange. In strategic co-offending, co-offenders exchange information; in instrumental co-offending, they trade services for rewards. A combination of these forms is also possible. In quasi-instrumental co-offending, offenders exchange services and social rewards (e.g., appreciation). According to this theory, co-offending takes place when *motivated* offenders *find* potential co-offenders that are *attractive* in terms of the goods that they are able to offer. Multiple proxies, like the accomplice's knowledge or skills, physical strength, or social capital (e.g., contacts or connections), can indicate a potential accomplice's attractiveness (McCarthy & Hagan, 2001; Weerman, 2003).

On the other hand, the collective rationality perspective on co-offending presupposes that people can reason collectively and recognise that their needs and desires can sometimes be satisfied by involving and benefiting others. Accordingly, cooperation becomes valuable for achieving personal and collective goals (McCarthy, Hagan, & Cohen, 1998). From a collective perspective of rationality, actors analyse the costs and benefits of committing a crime with others (similar to how *egocentric* actors do), but they recognise that their desires and goals rely on the decisions and actions of others, and, to some extent, bring benefits to others. This way of describing the decision to co-offend assumes that actors know that potential accomplices are capable of collective reasoning and that, when presented with the same information, both offenders will reach the same decision - i.e., engage in criminal cooperation (McCarthy et al., 1998).

Other factors such as adversity (e.g., living without a permanent shelter or starvation) might facilitate co-offending as extreme conditions might encourage people to reason collectively. Likewise, extreme situations might be conducive to increasing *trust* between unknown individuals who realise that help is needed to improve their position. For example, trusting another and deciding to commit a crime with them might be among the limited set of options this person has to quickly access the means to buy food. Following this perspective, co-offending results from a complex interaction between people that reason collectively and situational factors that can facilitate trust between individuals.

McCarthy et al. (1998), using data from a two-wave panel study of participants without a permanent shelter aged 25 years old or younger in Canada (N = 378), compared four models of criminal cooperation: *individualistic*, in which participants rarely received or offered help to commit a crime; *enlisting*, in which they received more invitations to co-offend; *recruiting*, in which participants extended more invitations to others to co-offend than those they received; and *collaborative*, in which participants made and received more offers to help in criminal ventures than the average, resembling collective reasoning. They found that the latter model of criminal cooperation is capable of explaining the participation of individuals in co-offences, specifically theft. In other words, youth with a 'criminally cooperative orientation' are more likely to commit theft than those with an individualistic approach to crime.

Nguyen and McGloin (2013) also tested the collective perspective of rationality in co-offending, using two samples of convicted felons in the United States. They used information from interviews with incarcerated offenders in Nebraska in 1998 (N = 700) and a survey of adult inmates in Colorado in 1996 (N = 646). The study sought to determine if variables such as employment status, financial needs (e.g., committing a crime to 'support my family' or 'having heavy debts') or drug-related adversity (e.g., 'needed money for my drugs') could explain co-offending. Through logistic regression models, they found that drug adversity problems (i.e., lacking the means to buy drugs) predicted co-offending; objective measures of financial necessity or self-declared financial motivations, on the other hand, did not. The underlying causes are not clear. It could be that drug users are impaired to commit crimes, which may lead them to rely on partners. Likewise, drug users could also happen to spend time with other users and take advantage of crime opportunities because of their lack of self-control.

The second group of theories perceive co-offending as an artefact produced by individual characteristics. It departs from the rational choice perspective and describes it as a by-product of underlying processes such as homophily - the tendency of people to connect with others with similar characteristics (McPherson, Smith-Lovin, & Cook, 2001). Since such characteristics include the disposition to offend (or other associated factors), homophily predicts that those prone to criminality will disproportionately associate and spend time with others who are also more likely to offend. Consequently, co-offending is expected even in the absence of a rational, well-planned decision; it simply emerges when predisposed individuals spend time together and stumble upon crime opportunities.

Adding to this perspective of co-offending, Felson (2003) contended that *offender convergence* might also explain co-offending. Offender convergence refers to the process by which routine activities bring together motivated offenders in places where they can seize criminal opportunities or design plans to execute crimes. The interactions among potential co-offenders occur at specific locations, labelled by Felson as *offender convergence settings*. Criminals cooperate in these settings by sharing information and resources necessary to start criminal ventures (Felson, 2006). Although not specifically stated by Felson, it is reasonable to expect to see individuals using online (e.g., virtual chat rooms and internet forums) and offline settings (or a combination of both) for these informal, unsupervised interactions. Choosing between these settings will depend on the types of crime offenders intend to execute and the level of planning required. According to Felson (2009), co-offending mostly relies on three circumstances: the concurrence of potential co-offenders at the same times and settings, the interaction between potential accomplices, and a substantial amount of socialising time. Regarding the latter, Reiss (1988) contended that, during social interactions, willing offenders are signalling their interest in finding potential accomplices and, simultaneously, trying to perceive the signals produced by others. Through this signalling process, co-offending will not always require substantial time for offenders to socialise since it can happen as soon as accomplices pick up these signals and decide to cooperate. As a result, co-offending might be described as a spontaneous event. For example, Alarid, Burton Jr, and Hochstetler (2009), drawing from interviews with 30 convicted co-offenders for robbery, observed that some described their involvement in crime-related activities as 'taken by surprise in a spontaneous opportunity' when committing crime (Alarid et al., 2009, p. 6). As described by the authors, in these instances, some accomplices might take a leadership role in the execution of the crime, and those 'taken by surprise' simply act as followers.

The third group of theories explain co-offending as a product of social and social-psychological processes. Social processes (or social mechanisms) influence the decision to co-offend more subtly than thoughtful, rational decisions. As explained by van Mastrigt (2017), 'social influence/process views on co-offending typically conceptualise group crime as the product of more implicit social dynamics and pressures that may operate outside of the conscious awareness and calculation of the actor' (p. 345). An example of a social mechanism is the expectation created among group members about specific behaviours of individuals in particular circumstances, such as cooperation during or after the execution of a crime. Some individuals might feel obliged to cooperate in a crime when, for example, a group member seeks help to avoid detection. The sense of belonging to a group creates an expectation of the necessity to help other members, even when circumstances involve criminal activities.

Similarly, the influence exerted by peers within social groups can explain why people co-offend: group members, especially adolescents, can learn social norms that lead to criminal behaviours (Weerman, 2014; Bruinsma, 1992). Norm acquisition (i.e., ideas of what is acceptable or expected), group identity, loyalty, fear, and status-seeking are among the social mechanisms that have a role in individuals' decision to co-offend (Warr, 2002).

Similarly, social psychological processes such as deindividuation and diffusion of responsibility can influence the decision to co-offend. Deindividuation refers to the state in which individuals embedded in groups are free from their limitations and self-control, and perceive that their actions will not be attributed to them (Festinger, Pepitone, & Newcomb, 1952). Through deindividuation processes, group members acquire a sense of anonymity that facilitates deviant behaviours (Diener, 1979). Deindividuation and the effect of anonymity diminish the capacity to self-evaluate behaviours, allowing people to depart from social norms and engage in criminal behaviours (Zimbardo, 1969; Spears, 2017). Likewise, diffusion of responsibility posits that individuals feel more responsible for actions executed alone than those carried out with others (Feldman & Rosen, 1978). The degree of responsibility attributed to individual and group actions allows offenders to diffuse or share the accountability of a group's wrongdoings. Due to this reduction in inhibition, it is hypothesised that individuals are more likely to engage in criminal acts when accompanied by others.

These social psychological processes can be accompanied by participants' efforts to neutralise the guilt of committing wrongdoings (Sykes & Matza, 1957), something that people might learn while interacting with peers (Sutherland, Cressey, & Luckenbill, 1992). From a social-process perspective, social structures might precede the decision to commit a crime. Those embedded in social groups can become potential accomplices once these mechanisms are in place and group members decide to seize a criminal opportunity. Accordingly, potential accomplices might have a vital role in the decision to co-offend through subtle processes derived from group dynamics.

The theories presented above were put forward to explain why people, especially adolescents, decide to co-offend. Further examination is required to determine which one of these perspectives explains why motivated offenders decide to co-offend and account for possible variations between, for example, juvenile and adult co-offenders. Collaboration in crime could derive from (apparently) rational decisions, the tendency of people to connect to those with similar characteristics (including their disposition to engage in criminal behaviour), and subtle social processes in which potential accomplices have a role in the decision to execute a crime. Despite the theoretical propositions developed so far about why people commit crimes in groups, the number of theories about co-offending is scarce compared to theories on crime and criminal behaviour in general (Weerman, 2014), and there have been few attempts to refine or falsify these theories empirically (van Mastrigt, 2017).

2.3 Accomplice Selection

Another key decision in co-offending is accomplice selection, and a number of theories have also been proposed to explain this process. One of these frames the search for co-offenders as a rational process whereby offenders try to maximise benefits and reduce costs when selecting accomplices. To achieve this balance, offenders evaluate potential partners based on their perceived trustworthiness (to minimise the risk of betrayal) and the likelihood of the individual maximising the expected benefits from the criminal venture (Tremblay, 1993). This evaluation implies judging the *criminal capital* of their potential accomplices, which includes the skills, information, and contacts deemed beneficial for successfully executing a crime (McCarthy & Hagan, 2001; McCarthy et al., 1998). Deciding to co-offend and searching for suitable accomplices might not be sequential activities. The decision to co-offend and co-offenders' availability (including their criminal capital) might feed one another, affecting the decision as to whether or not co-offend and the types of crimes they might attempt to execute (van Mastrigt, 2017).

Accomplice selection can also occur spontaneously when people signal their readiness to commit a crime to potential partners (Reiss, 1988). This could happen, for example, among a group of friends that decide to commit robbery as they stumble upon a suitable opportunity (Alarid et al., 2009). In these scenarios where co-offending seems spontaneous, individuals act without previous planning or a thorough assessment of the risks and benefits involved. From this perspective, accomplice selection seems impulsive and highly dependent on situational factors. For some crimes, the set of potential accomplices also depends on geographical factors because offenders must converge not only in time but also in space. Hochstetler (2001), using information from interviews with 50 male offenders on community supervision, reported that some participants described the signalling process of verbal and non-verbal cues as evolving. Accordingly, sending and receiving the prompts needed to co-execute a crime requires some time to send and receive these signals, even though co-offending sometimes seems spontaneous.

In addition to the differing explanations about why offenders might prefer certain accomplices, offenders' immediate geography and social networks might limit the pool of potential accomplices from which they can choose. For example, *propinquity* can explain how offenders end up with their accomplices: by being close to each other, motivated offenders are likely to make contact and communicate their intentions to potential partners who are nearby (Reiss & Farrington, 1991). Such geographical constraints can also be seen in terms of offenders' *activity-spaces*: the places where they spend time in the course of work, leisure, and other habitual activities (Brantingham, Brantingham, & Andresen, 2017). Hence, motivated offenders are more likely to co-offend with those who coincide in these locations.

Concerning the effect of social settings on the formation of co-offending relationships, research has shown that siblings, friends, acquaintances, and work colleagues tend to co-offend more than groups of strangers (Sharp, Aldridge, & Medina, 2006; Reiss & Farrington, 1991). This is consistent with the proposition that offenders select their accomplices from a biased set of options since they tend to be part of the social networks created through interactions in settings like schools, workplaces, families, or neighbourhoods (Warr, 1996). The limitations posed by social settings and the principle of homophily, thus, might explain why co-offenders tend to be similar in age and sex (Carrington, 2015). These limitations offer an additional description of co-offending. There might be instances in which the presence of a potential accomplice, particularly one with specific skills or knowledge, has a central role in the initial decision to offend (van Mastrigt, 2017). In this regard, social and geographical constraints can affect both the decision to co-offend and how accomplices are selected, as those who are available might influence one or both decisions - though, to be clear, it is not being suggested here that there is an orderly, fixed process in which motivated offenders first decide to co-offend and then start searching for accomplices.

As it will be discussed in Chapter 6, some of the mechanisms that explain how accomplices are selected can illustrate how *co-offending networks* - a concept outlined in Chapter 3 - evolve. For example, offenders with attractive criminal capital might tend to be selected more often (or recruit others more often), and this may drive the networks' growth, with a few individuals with special skills or abilities acting as 'hubs' for connections between multiple offenders. The trust created through initial interactions can also explain how networks evolve, as co-offending networks can expand through repeated interactions between known offenders.

As with the theories about why people decide to co-offend, there is no widely accepted perspective on co-offender selection. The interplay between explicit decisions to minimise risks and increase benefits, and the implicit effects of geographical and social restrictions, might explain the decisions made by offenders regarding their partners in crime (van Mastrigt, 2017). The particular role of social networks in the decision to co-offend and the selection of accomplices has been discussed to a limited extent. For example, the evidence presented by Sarnecki (2001) regarding a co-offending network of juvenile offenders (age 20 or under) in Stockholm between 1991 and 1995 supports the claim about the role of homophily in accomplice selection ($N = 19,617$). It was observed that 76% of pairs of co-offenders (or dyads) were comprised of people of the same age (± two years), while 89% were comprised of male offenders. However, the skewed distribution in the sample included in this study might explain these findings:

85% of the participants were males, and the study only included people within a ten-year age range (10-20). Apart from this study, however, attempts to refine or falsify accomplice selection theories using information conveyed by social networks are limited.

2.4 Characteristics of Co-offenders

Co-offending studies have paid particular attention to co-offenders' age and, to a lesser extent, sex, as determinants of the tendency to co-offend. Overall, research has shown that the tendency to collaborate with others during the execution of crime correlates strongly with offenders' age: adolescents tend to co-offend more than adults; hence, adults tend to be solo offenders (Reiss, 1988; van Mastrigt & Farrington, 2009; van Mastrigt, 2014; Weerman, 2003). For example, in the Cambridge Study in Delinquent Development ($N = 411$), Piquero, Farrington, and Blumstein (2007) reported that 75% of the crimes committed by males (aged 10-13) included two or more offenders, but solo offending became the norm once participants reached 20: 72% of the crimes committed between the ages of 37 and 40 were solo offences.

Some authors have hypothesised why youths are more likely to co-offend than adults. Carrington (2009) argued that adolescents tend to co-offend more because the lack of autonomy among youth drives them to share more activities with peers, including crime-related activities. Similarly, Warr (1996, 2002) contended that youths, compared to adults, spend more time with peers due to the lack of work and family-related commitments and are more susceptible to peers' influence in their behaviours. Furthermore, the perceived rewards from interactions with groups of peers that engage in antisocial behaviours are higher for young offenders than for adults (Weerman, 2003). The changes experienced by the latter in the early stages of adulthood (e.g., establishing solid relationships, starting stable employment, or acquiring financial responsibilities) can also explain this difference: adults have more to lose if they engage in criminal behaviours and are apprehended (though, to be clear, this argument is applicable both for co-offending and solo offending) (Catalano & Hawkins, 1996; Kosterman et al., 2014). The accumulation of criminal capital through previous experiences can also explain why adults tend to offend alone. As their criminal careers progress, offenders will gain more criminal capital; consequently, accomplices might become redundant as few of them will provide an added value (McCarthy et al., 1998; McCarthy & Hagan, 2001; Reiss & Farrington, 1991).

However, some studies using extensive incident-based data have shown that solo offending is common among young offenders and group offending is a trait also displayed by adult offenders (Carrington, 2002; Stolzenberg & D'Alessio, 2008; van Mastrigt & Farrington, 2009; Andresen & Felson, 2012). It is unclear why these studies have shown different trends (van Mastrigt & Farrington, 2009; van Mastrigt & Carrington, 2018; van Mastrigt, 2014). In any case, Andresen and Felson (2012) contended that, overall, research shows that co-offending is a widespread form of offending among young offenders that needs to be better understood. Similarly, van Mastrigt and Carrington asserted that 'the aggregate age-co-offending curve typically rises to a peak in mid-adolescence, decreases rapidly through the twenties, and reaches a stable low later in life, a pattern observed fairly consistently across samples and when controlling for both gender and crime type' (2018, p. 131). Namely, compared to adults, adolescents are more likely to offend in groups once they have decided to engage in criminal behaviour. This finding is consistent for different periods and some countries (van Mastrigt, 2014).

Regarding offenders' sex, the overall evidence produced so far relates primarily to young offenders. It shows that females tend to co-offend more than males, controlling for crime types and age (van Mastrigt, 2014; Reiss, 1988; Pettersson, 2005; Sarnecki, 1990). The difference between the co-offending rates of males and females, however, tends to be less than ten percentage points (van Mastrigt, 2014; Carrington, 2002). The finding that age and crime type cannot wholly explain the difference in co-offending rates between males and females implies that there is a difference between sexes in terms of their tendency towards collaboration (van Mastrigt & Farrington, 2009), and this can also be seen in the types of groups in which each participates. Both males and females tend to co-offend in groups of two, but males are more inclined to offend with larger groups. For example, Carrington (2002) observed that more than 80% of the incidents recorded by police in Canada between 1992 and 1999 were related to solo offenders ($N = 2,891,695$): the police recorded 76% of the incidents involving males as solo offences, while the proportion of incidents concerning females reached 74%. Females tended to co-offend more than males in groups of two (14.6%, males; 18.2%, females), but males co-offended more in groups of three (5.4%, males; 4.5%, females) or four (2.1%, males; 1.7% females) individuals. The author did not include information about the statistical significance of the differences between males and females.

2.5 Crime Types and Scale of Co-offending

Research shows that co-offending is common in burglary, arson, robbery, auto theft, minor thefts, possession of stolen property, vandalism, and gambling, and, to a lesser extent, in sexual assaults, drug possession, drink-driving, and administrative offences (van Mastrigt, 2017; van Mastrigt & Carrington, 2019; Carrington, 2014). Co-offending in crimes like burglary is consistent with the rational perspective of co-offending. These crimes require, to some extent, a division of labour; therefore, liaising with an accomplice seems to be a rational decision for a successful execution (van Mastrigt & Farrington, 2009). On the other hand, vandalism can be explained by the social exchange theory of co-offending. Offenders, especially adolescents, may engage in crimes like vandalism to access social rewards like recognition (Weerman, 2003).

Co-offending can also play a role in determining the outcomes of crimes and have implications for the consequences for the victims. For example, Carrington (2002) and Alarid et al. (2009) showed that co-offenders were more likely to use firearms or other weapons to commit their crimes than solo offenders, increasing victims' risks. Similarly, co-offending groups were more likely to injure their victims than solo offenders (Lantz, 2018). McGloin and Piquero (2009), using a random sample of 18 years old or younger delinquents arrested in Philadelphia in 1987 ($N = 400$), observed that individuals who tended to offend in larger groups were likely to commit more violent offences, with an increase of 1 in the average number of co-offenders increasing the expected count of violent group offences by 9.6% ($n = 335$, participants with at least one co-offence). They also observed that the odds of an individual's first group offence being violent increased by 33%

for every additional co-offender participating in the event (n = 235, participants linked to a violent crime).

Concerning its scale, some criminologists have considered co-offending a 'criminological fact' due to the high proportion of crimes committed by two or more individuals. Early reports revealed that co-offending rates - i.e., the proportion of offences committed by two or more offenders relative to the total number of crimes - were high across a range of settings (Breckinridge & Abbott, 1912; Shaw & McKay, 1931), and further findings reported decades later confirmed that co-offending was prevalent (Reiss, 1988, 1986; Reiss & Farrington, 1991; Warr, 1996). However, recent studies argue that co-offending is less widespread than previous studies reported. Carrington (2014) summarised 14 studies published from 1931 to 2011 and found that co-offending rates ranged between 10 and 70%. Similarly, recent studies show significant variability in co-offending rates: 6% in Norway (Andersen, 2019) and 35% in Denmark (Frydensberg, Ariel, & Bland, 2019). The variation in this rate can be explained by the multiple sources of information used to measure co-offending, which included police records, court records, victim reports, and self-reports (van Mastrigt & Farrington, 2009). For example, offenders self-reporting co-offences might over-report their participation to show how well-connected or important they are. Likewise, official records, such as those kept by the police about those who have been arrested, have inherent limitations that can bias the estimation of co-offending rates. It is possible to identify co-offenders using arrest records by identifying those who were co-arrested at the same time and place for their alleged participation in events connected to a particular crime (or set of crimes). But if two co-offenders are arrested at a different time, it would not be possible to identify them as co-offenders since they were not arrested at the same time. Moreover, the inclusion of crime types that are different from those that intrinsically require collaboration or division of labour, and the consideration of offenders from different age ranges - not only juveniles, as in early studies - might explain the variability in co-offending rates (Grund & Morselli, 2017).

Reiss (1988) suggested that, throughout their criminal careers, offenders tend to alternate between solo offending and co-offending. Given its dynamic nature, an alternative way to estimate the scale of co-offending is through *co-offending participation rates*. These rates measure offenders' participation in co-offences during a specific time frame. In co-offending rates, crimes are the unit of analysis - e.g., 20% of the crimes reported within a specific period were executed by co-offenders. In co-offending participation rates, individuals become the unit of analysis - e.g., 30% of the offenders considered in a study participated in a co-offence within a two-year window. Carrington (2014) summarised the evidence produced until 2014 and observed that between 30% and 89% of the offenders in Canada, Sweden, the UK, and the USA liaised with other offenders at some point during the study periods. For example, Pettersson (2005), using data recorded by the police about violent offences reported in Stockholm in 1995, observed that 89% of the 1,253 juvenile suspects included in the study committed at least one crime with another person in that year.

In short, the evidence indicates that co-offending is related to specific crime types. As mentioned in Chapter 1, the findings produced so far about co-offending are related to a small group of countries (Canada, Sweden, the UK, and the USA); therefore, these findings can only be generalised to some extent to high-income countries. Moreover, the findings concerning co-offending rates seem to vary. The studies published in the last decades that have included multiple crime types and offenders from different age ranges (although the scope of countries considered continues to be limited) have moderated the claim that co-offending is a 'criminological fact'. Likewise, co-offending participation rates seem to vary.

Despite the variability in these rates, co-offending remains relevant for its theoretical and policy implications. Regarding the latter, the dynamic nature of co-offending can explain changes in crime rates (Andresen & Felson, 2010; Zimring, 1981). Incapacitation of offenders through traditional criminal court procedures may reduce crime if the removal of offenders deters their accomplices, who are then less likely to commit crimes on their own or with cooperation from new accomplices (Reiss, 1988). Similarly, crime takes place not only when suitable targets and motivated offenders coincide in the absence of a capable guardian, as suggested by Cohen and Felson (1979), but also when offenders are capable of finding appropriate partners when required (Tremblay, 1993). In theory, the incapacitation of an offender can potentially reduce crime by diminishing the odds of motivated offenders finding suitable partners (Andresen & Felson, 2010). The incapacitation of offenders might also prevent crime if their removal disrupts the flow of criminal capital within the network of potential accomplices (e.g., those removed are unable to teach their associates the required skills to continue offending). The disruption of *co-offender convergence settings* can also contribute to changes in crime rates by impeding motivated offenders from finding suitable partners (Andresen & Felson, 2010). Chapter 8 addresses in more detail the implications for crime prevention derived when studying the evolution of co-offending networks.

2.6 Co-offending Groups

The term 'co-offending group', although not explicitly defined in the literature, refers to the organisational layout created by individuals when they execute a crime or a series of crimes together. Within these groups, offenders can play different roles, depending on their involvement in bringing the group together and their leadership with respect to the crime itself. Furthermore, co-offending groups can vary in their longevity, with most tending to be small, unstable, and, consequently, short-lived (Weerman, 2003, 2014; Warr, 2002, 1996; Carrington, 2002; McGloin & Thomas, 2016; McGloin & Piquero, 2010; van Mastrigt, 2017).

When co-offending does not arise spontaneously, groups form when a person acting as a recruiter (or instigator) brings together other accomplices who act as followers (Reiss, 1986). The roles of instigators and followers are not fixed: offenders can act as joiners or recruiters in different criminal ventures depending on situational factors and their criminal capital. For example, if a former follower has information about a criminal opportunity through her contacts, she might try to recruit those accomplices whose skills match the particular crime. Accordingly, disparities in criminal capital allow offenders to change their roles. In turn, these disparities and changes in roles explain why recruiters tend to be older than followers (Van Mastrigt & Farrington, 2011).

Co-offending groups are typically small since offenders are likely to execute crimes with only one accomplice (Reiss, 1988; Reiss & Farrington, 1991). Carrington (2014) summarised findings produced before 2011 regarding the size of co-offending groups and observed that those in Canada and England followed a similar pattern, while those in the USA displayed a different behaviour. In Canada and England, groups of two offenders represented 70% of the groups, while 17% to 20% had three offenders, and less than 9% had four individuals. In the USA, almost 40% of the groups had two members, 29% had three, and 31% had four members. According to Carrington (2014), variations in the data used for each country can explain these differences. Primary studies in Canada and England used police records. In contrast, those from the USA used incidents of violent criminal victimisation that included the concept of 'involvement', which was not precisely defined. Despite these inconsistencies, the evidence shows that co-offending groups, in general, tend to be small. The size of co-offending groups also correlates with offenders' age: as offenders get older, the size of these groups declines (Reiss, 1988; Warr, 2002). Therefore, large co-offending groups are rare once offenders reach their mid-twenties, the age range in which they tend to switch to solo offending if they continue committing crimes (Carrington, 2002).

The instability of co-offending groups partly results from co-offenders' tendency to regularly change associates, which often limits criminal partnerships to single events (Reiss & Farrington, 1991; Charette & Papachristos, 2017). Exceptionally, individuals will continue offending with the same accomplices due to the trust built through previous interactions. The individuals that repeatedly co-offend together tend to be similar in terms of their demographic characteristics (e.g., age, sex, race), have more prior arrests, and offend with larger groups (Charette & Papachristos, 2017; McGloin, Sullivan, Piquero, & Bacon, 2008).

Group instability also relates to offenders belonging to multiple groups (Reiss, 1988; Sarnecki, 1990; Warr, 1996). Offenders associated with more than one group have access to more potential accomplices and criminal opportunities (Tremblay, 1993). The decisions made throughout offenders' criminal careers also account for the instability of these groups: as explained, offenders shift between solo and co-offending depending on their criminal experience, the opportunities that arise, and the availability of suitable accomplices (Reiss & Farrington, 1991; Tremblay, 1993; Reiss, 1988).

Due to the instability of criminal partnerships, co-offending groups tend to have a brief lifespan. Based on this frequently observed characteristic among co-offenders, some have questioned whether the notion of 'co-offending groups' is meaningful. Yablonsky (1959), for example, while analysing gangs in New York City, questioned the existence of co-offending groups. He contended that social groups (or 'collectivities') lay in a continuum with crowds and mobs on one side and highly organised groups on the other. Given their short lifespan, co-offending groups lay in the middle of this continuum since they do not resemble mobs or highly-organised groups. 'Near groups', as he referred to *co-offending groups*, tend to have a diffuse role definition, minimal consensus regarding norms, shifting membership, and limited membership expectations. In a similar vein, Warr concluded four decades later that '[co-offending] groups are so short-lived that it may make little sense to even speak of delinquent groups at all' (Warr, 1996, p. 33). Chapter 7 revisits the concept of co-offending groups and proposes a network approach to identify them in large networks modelling the interactions between offenders and criminal events. It also uses this information to assess the extent to which these groups specialise in certain crimes, a feature not explored so far in adult co-offending groups.

2.7 Summary

This Chapter reviewed theories about why people co-offend and how they choose their accomplices. It also summarised the evidence about co-offenders' characteristics, the crime types in which this phenomenon is prevalent, and the co-offending groups' traits (see Table 2.1 for a summary). Van Mastrigt (2017) contended that, although these theories address two aspects of co-offending separately, the decision to co-offend and accomplice selection should not be regarded as two different or sequential processes. Deciding to co-offend and selecting accomplices are intertwined: the availability of a suitable accomplice may determine whether some criminal opportunities are taken, while other opportunities may only arise via another individual. Since exposure to potential accomplices will often come primarily via social networks, this implies that the shape and composition of these networks will play a large role in these decisions. Accordingly, some of these theories can suggest what behaviours co-offending networks might exhibit. In this regard, and as mentioned in Chapter 1, Bichler (2019) presented the 'theory of networked opportunity'. This theory tries to understand how social networks shape the interactions between offenders and their surroundings, and how these interactions are conducive to opportunities for crime. Following this theory, offenders can access information and individuals through their social networks that might affect their decisions regarding their participation in criminal activities.

Motivated by Bichler's theory, Chapter 5 looks into the role of social networks in accomplice selection by studying the likelihood of two offenders committing a crime together if they share an accomplice. Triadic closure, as this trait is referred to, is closely related to the constraints posed by social networks and social processes when offenders search for accomplices. If these limitations occur, co-offending networks are expected to exhibit some level of triadic closure. Likewise, Chapter 6 outlines the similarities and differences between the theories about how offenders select their accomplices and the mechanisms that explain how social networks evolve. That Chapter provides evidence about the likelihood of offenders re-selecting the same accomplice for new criminal ventures, contradicting the findings mentioned above about the tendency of offenders not to reuse accomplices. This finding can be interpreted from a rational choice perspective: offenders are inclined to re-use accomplices to reduce the costs associated with searching for new candidates. Sticking with the same partner can also be considered a rational decision because the combined criminal capital between co-offenders is required to continue exploiting similar criminal opportunities. This, in turn, would suggest that some co-offenders will re-offend, and criminal specialisation is likely to be observed in co-offending relationships. In this regard, Chapter 7 explores adult co-offending groups' tendency to become specialists (or generalists).

Table 2.1: Theories and findings related to co-offending

Aspects	Theories / Findings
Decision to Co-offend	a. Rational (bounded) decision (reduce costs, increase benefits based on the information that is available) b. Co-offending as an artefact (homophily) c. Social and social-psychological processes (norm acquisition, deindividuation)
Accomplice selection	a. Rational decision (accomplice evaluation to maximise benefits) b. Spontaneous selection (signalling process between accomplices) c. Limitations posed by geography and social environments
Characteristics of co-offenders	a. Mixed findings: adolescents are more likely to co-offend than adults b. Small difference between males' and females' co-offending rates
Crime types and scale	a. Prevalent in some crime types (e.g., burglary, arson, robbery, and minor thefts) b. Co-offenders are more likely to use weapons c. Co-offending rates: 6 to 70% d. Co-offending participation rates: 30 to 89%
Co-offending groups	a. Groups tend to be small, unstable, and short-lived b. Recruiters and followers create co-offending groups c. Co-offending network analysis tends to be static

Chapter 3

Network Science: Concepts and Definitions

3.1 Overview

Research produced at the intersection between network science and crime is significant as it has allowed researchers to address old questions using new approaches (Bouchard & Malm, 2016). 'What role do peers have in the aetiology of crime?' (e.g., Gallupe, Bouchard, & Davies, 2015), 'How are illegal markets organised' (e.g., Malm & Bichler, 2011) or 'How are criminal organisations structured?' (e.g., Morselli, 2009) are some examples of the questions revisited using network science tools and theories. The advancement in network science and the availability of crime-related data has contributed to establishing 'networked criminology' - a subfield of studies that use network tools and principles to study crime (Bichler, 2019; Papachristos, 2011). This Chapter introduces the reader to some network science concepts used in the studies presented in Chapters 5 - 7.

3.2 Networks: definitions and key concepts

Networks are at the core of networked criminology. In general, networks are simplified representations of systems composed of discrete elements, and they capture the fundamental connections between the entities comprising such systems (Newman, 2018). Researchers can use networks to model the interactions of a diverse range of systems, such as the world trade system (which country sells what to other countries), the communication of sexually transmitted diseases (who infects whom), or the air transport system (airports connected by planes flying from destination A to B) (Barabási, 2016). In crime science, networks can represent the interactions between individuals executing crimes, as in the case of co-offending. Likewise, communication patterns (i.e., who talks to whom) between those participating in illegal activities can be modelled using networks. Organised crime and terrorism researchers have adopted the latter approach to describe the internal structure of criminal groups (e.g., Campana, 2011; Krebs, 2002; Morselli, 2009; Malm & Bichler, 2011).

Social networks - as opposed to technological, biological, or transport networks - focus on the social interactions among people, with a view to understanding how these connections might explain collective and individual behaviours (Wasserman & Faust, 1994). Through a social-network approach, individuals and their actions are seen as interdependent: the connections create conduits through which tangible and intangible resources flow between people. These resources, in turn, can affect individuals' *norms* (i.e., expectations about what a person considers appropriate or acceptable) and behaviours (Christakis & Fowler, 2009). The idea of values and informal rules circulating within a group of people, as explained in Chapter 2, is paramount in the theories that explain co-offending as a result of social and social-psychological processes.

In a social network, each individual's position can be understood in terms of their connections and those of their neighbours. The location of individuals in the network, in turn, facilitates or constrains their behaviours, ideas, or opportunities (Borgatti, Everett, & Johnson, 2018). For example, in a network modelling sexual encounters, a node with a higher number of connections represents a person with more sexual partners than the rest. Given this position, this person will have access to more opportunities for sexual encounters and, at the same time, increase their chances of contracting a disease if someone in the network acquires an illness (Christakis & Fowler, 2009). Similarly, offenders with multiple connections in a criminal network are likely to be prolific co-offenders, but will also have increased visibility, simultaneously augmenting the risks of getting arrested by law enforcement agencies (Morselli, 2009).

Network scientists have developed numerous concepts and metrics to examine the properties of networks (see Borgatti, Mehra, Brass, and Labianca (2009) and Barabási (2016) for a review of this field). The advancements in this field have been mainly achieved by studying the properties of mathematical structures called *graphs*. Graphs consist of a set *nodes* and a set of *edges* (or links), where each edge represents a connection between a pair of nodes (Essam & Fisher, 1970). The nodes depict the system's entities - e.g., countries, sexual partners, airports, or offenders - and the edges represent the relationships occurring among them. In a co-offending network, each node represents an offender and an edge connecting two offenders typically represents their co-participation in a criminal act.

Edges can specify the direction of the relationship (e.g., A selects

B), and graphs with edges of this form are referred to as *directed* graphs. Edges can also be *undirected*, implying the absence of directionality (e.g., A meets with B) or that the direction is unknown. In addition, edges can have an associated weight, representing the intensity or frequency of the interaction between nodes, and graphs with this property are referred to as *weighted* graphs. It is also possible for multiple edges to exist between a pair of nodes, and graphs in which this is the case are defined as *multigraphs* (Bollobás, 1998). Either weights or multiple edges can provide an indication of the strength of a relationship: edges connecting pairs of nodes with an intense interaction will be 'heavier' - or have multiple edges, in the case of a multigraph - than those connecting pairs of nodes with a less intense interaction. The analysis presented in Chapter 6 relies on the information conveyed by edges to study the evolution of co-offending networks. In that context, edges' directionality represents the accomplice selection process (i.e., offender A recruits/instigates B), and their weights represent the number of crimes co-executed by pairs of co-offenders.

Figure 3.1 presents an example of an undirected co-offending network. This network has five nodes or offenders (A, B, C, D, and E) and four weighted edges (A-B, A-C, C-B, and C-D). This network shows that A and B co-executed three crimes, while the other pairs only co-executed one each. E represents a solo offender since they do not share an edge with any other offenders.

Pairs of connected nodes, referred to as *dyads*, are the building blocks of networks. The example presented above has four dyads (A-B, A-C, B-C, and C-D). A network is essentially the union of multiple dyads, together forming complex structures that capture the interactions taking place within a system (Borgatti et al., 2018). By examin-

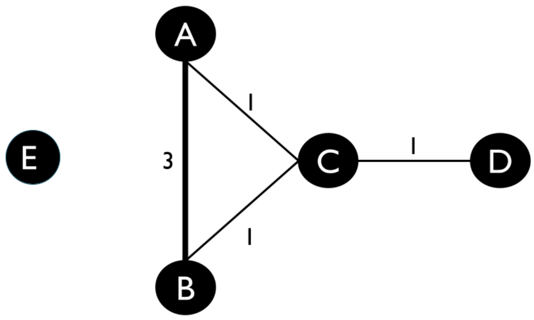


Figure 3.1: An undirected network with five nodes (A, B, C, D, E), four weighted edges, and two sets of connected nodes known as components (see below for a detailed definition): i) A, B, C, and D; and ii) E

ing these building blocks, it is possible to identify, for example, the number of direct connections a node has and the characteristics of its neighbours (e.g., if they are well-connected nodes). *Triads* are another fundamental sub-structure within networks, comprising three nodes (e.g., A-B-C, A-C-D, or B-C-D). Examining them provides information such as the degree of *transitivity* (or closure) observed in the relationships between nodes (Newman, 2018). A transitive relationship implies that if A is connected to both B and C, then B and C are likely to be connected. In a crime-related context, transitivity would imply that if A independently co-offended with B and C, then it is likely that C and B would end up co-offending together, given their mutual connection to A. In a transitive relationship, A, B, and C create a closed triangle such as the one presented in the proposed example. Multiple network statistics such as clustering coefficients (explained below) are based on triads (Wasserman & Faust, 1994). The study presented in Chapter 5 relies on this idea of transitivity and closure in social networks to explore accomplice selection theories further.

Connections between consecutive pairs of nodes create conduits through which resources can travel around a network. A *walk* is a route composed of nodes and edges that starts and ends in a node. In the example presented above, one walk could be between A, C, and D, or A, B, and C. A *paths* is a walk in which no nodes and edges appear more than once (Wasserman & Faust, 1994). They can provide information about how nodes are connected and about the network itself. For example, it is possible to identify the shortest path connecting a pair of nodes (also referred to as a *geodesic*) or measure the 'diameter' of the network, which corresponds to the largest geodesic (the 'longest, shortest path') between any pair of nodes. The network in the proposed example has a diameter equal to 2.

Network analysis uses the elements described so far to observe and measure properties of node, groups of nodes, and networks as a whole. The first level of analysis focuses on the connectivity patterns of individual nodes. There are numerous metrics and measures to assess the properties of nodes, such as degree centrality, closeness centrality, and betweenness centrality. *Degree centrality* measures the number of edges (or connections) a node has. In the network presented above, the degree centrality of C is equal to 3; B and A, 2; D, 1; and E, 0. For directed networks, the number of incoming and outgoing edges can be measured separately, as the in-degree and out-degree, respectively.

Paths in a network can also provide information about how close nodes are to each other, which is the basis of *closeness centrality*. Following Newman (2018), the mean distance l_i from a node i to every other node is defined as

$$l_i = \frac{1}{n-1} \sum_j d_{ij}, \tag{3.1}$$

where n is equal to the number of nodes in the network and d_{ij} is the distance between i and j. The closeness centrality of a node i, c_i, is defined as the inverse of l_i:

$$c_i = \frac{1}{l_i} = \frac{n-1}{\sum_j d_{ij}} \tag{3.2}$$

In the proposed example, this statistic will only consider nodes A, B, C and D, since E is disconnected. This node can have an infinite distance from the other nodes, meaning its closeness centrality will be equal to 0, and, accordingly, it is not a central node in the network. C has the highest closeness centrality (1), followed by A and B (3/4), and D (3/5). In this regard, C would be in a slightly better position to efficiently spread information among those in the network since it can more easily reach A, B, and D.

Betweenness centrality measures the extent to which a node is part of the shortest paths connecting pairs of other nodes (i.e., *geodesics*). The betweenness centrality of a node is calculated by counting the number of times it lies on the shortest paths (i.e., *geodesics*) between pairs of other nodes in the network. Betweenness centrality, b_i, can be defined as

$$b_i = \sum_{st} \frac{\sigma_{st}(i)}{\sigma_{st}}, \tag{3.3}$$

where the sum is over all pairs of connected nodes s and t, σ_{st} is the number of shortest paths between s and t, and $\sigma_{st}(i)$ is the number of shortest paths between s and t which contain i (Newman, 2018). Here, again, C has the highest betweenness centrality, 2, as it lies in the geodesics connecting A-D and B-D. Since no geodesics pass through A, B, D or E, their score is 0. Individuals with a high betweenness centrality can act as gatekeepers or brokers because they can control the flow of resources circulating in networks. In the proposed example

(Figure 3.1), D relies on C to know about the criminal opportunities devised by A or B, and *vice versa*.

Network analysis can also be centred on specific assemblies of nodes. *Cliques* are among those substructures. They are subgraphs in which all pairs of nodes share a link. From a sociological perspective, cliques denote the existence of close-knit groups. In a crime-related context, cliques might resemble groups in which people share social norms and behaviours. Accordingly, people offending in cliques can have a sense of security since they all know each other, and, therefore, there might be fewer incentives for betrayal. Moreover, in cliques, every node has access to the information circulating within cliques. Accordingly, cliques can efficiently execute crimes as coordination improves due to the lack of brokers or gatekeepers and the speed at which information can travel (Morselli, 2009).

Note that the sociological notion of cliques (i.e., close-knit groups sharing norms and values) might not necessarily apply to co-offending groups. As explained in Chapter 2, co-offending relationships may emerge spontaneously, and participants may not know each other; thus, they may share different norms and values, and their incentives for avoiding betrayal may differ. Nonetheless, as discussed in Chapter 7, the notion of cliques can be extended to bipartite networks to identify two or more offenders that have committed multiple crimes together, denoting the existence of co-offending groups.

Components are also subsets of nodes: a component is a group of nodes such that all nodes are reachable from each other via paths, and to which no additional nodes could be added while maintaining this property. If it is possible to 'walk' around the network and visit all the nodes, then this network will have one single component and be referred to as a *connected* network. If it is impossible to visit all the nodes - such as E in the above example - then the network will have multiple components. A network with multiple components is called a *disconnected* or *fragmented* network. One particularity of components is that they do not need a minimum number of nodes: isolated nodes like E are considered as a component.

Numerous studies have shown that co-offending networks are highly fragmented (e.g., McGloin, 2005; Sarnecki, 2001; Brantingham, Ester, Frank, Glässer, & Tayebi, 2011). For example, da Cunha and Gonçalves (2018), using intelligence records collected by the Brazilian Federal Police about 23,666 offenders and suspects related to multiple types of crimes committed in 2013, observed that the network contained 3425 components. The largest connected component contained 40% of the nodes (n = 9,887). Similarly, Charette and Papachristos (2017) found that the co-offending network comprising all offenders who were arrested with at least one other person by the Chicago Police Department between 2006 and 2013 contained 181,615 individuals and had 25,339 components. The largest component contained 63% of the nodes. Despite these findings of components containing a considerable proportion of offenders, there is no information about the underlying processes that led to the emergence of large connected components in these co-offending networks. Chapter 6 tries to tackle this question by studying the evolution of three co-offending networks.

Networks can also be partitioned into *communities*. A community is a set of nodes which can be meaningfully grouped because they are more likely to connect among themselves than to other assemblies in the network (Barabási, 2016). They convey information about the structure and organisation within a network (Newman, 2018). As massive sets of crime-related data are becoming available, researchers have started using community detection algorithms to identify communities in criminal networks (e.g., Bahulkar, Szymanski, Baycik, & Sharkey, 2018; Robinson & Scogings, 2018). For example, da Cunha and Gonçalves (2018), using the Louvain method for community detection, observed that the largest component of the co-offending network, with 9,887 offenders, contained 91 communities.[1] Chapter 7 presents an alternative way to identify meaningful substructures in co-offending networks and highlights the shortcomings of using communities to assess the degree of criminal specialisation of co-offending groups.

When networks are examined at the general level, the properties of the network as a whole are considered. This includes, for example, the total number of nodes in the network (or its *order*) and its *density*. Networks' density provides information about the probability that, if a pair of nodes is chosen at random, an edge will be present between them (Newman, 2018). This probability (δ) is equivalent to the number of edges present as a proportion of the total number of possible edges the network could have (if every pair of nodes was connected). It is defined as

$$\delta = \frac{2m}{n(n-1)}, \tag{3.4}$$

where m is the number of edges and n is the number of nodes. Values of δ close to 0 indicate low connectivity (i.e., the chances of observing an edge between two randomly-chosen nodes are low). In

[1]This algorithm uses the measure of modularity, which is similar to assortativity mixing by degree (see below). Both assess the extent to which nodes with similar characteristics share an edge. The Louvain method optimises the network's modularity by assigning individual nodes to unique groups. Then, the nodes are moved between groups with the aim of increasing the overall modularity of the network. If no further movements can increase the modularity, then groups are merged. Once it is not possible to further increase the modularity of the network, this algorithm stops, and the resulting groups represent the communities of nodes in the network (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008).

contrast, those close to 1 suggest that a high proportion of all possible edges are present. As mentioned before, information can travel fast in well-connected networks and, by definition, the degree centrality of nodes in dense networks will tend to be similar (i.e., large numbers of connections will not be concentrated on a few actors). The network presented in Figure 3.1 has a relatively low density ($\delta = 0.4$) since E is disconnected and edges between A-D and B-D are missing.

Another important characteristic of networks is the distribution of degree centrality across the nodes. This distribution provides the probability that a particular node chosen randomly has a specific degree of centrality. For a given degree k, this probability (ρ_k) can be defined as

$$\rho_k = \frac{\tau(k)}{n}, \tag{3.5}$$

where $\tau(k)$ is the number of nodes with degree centrality k, and n is the number of nodes in the network. Many real-world networks, across different settings, tend to show a right-skewed degree distribution, similar to the example in Figure 3.2. It indicates that a small fraction of nodes have a large degree of centrality (i.e. are connected to many other nodes), while the majority share edges with few others (Barabási, 2016).

Brantingham et al. (2011), using arrest records from a 5-year time frame in the Province of British Columbia (Canada), observed that the degree distribution in a co-offending network, controlling for different types of crimes, displayed a similar pattern to the one presented in Figure 3.2. Most offenders were only connected to a few others, while a small fraction had numerous connections. Such findings can provide helpful information to law enforcement agencies to identify offenders acting as criminal ‘hubs’, attracting many accomplices. However, as discussed in Chapter 6, it is not possible to distinguish the underlying mechanisms that describe the evolution of a network by only considering the degree distribution. A better approach is to continuously observe how the network grows and consider multiple mechanisms that explain how new connections are created - the study presented in Chapter 6 follows this approach.

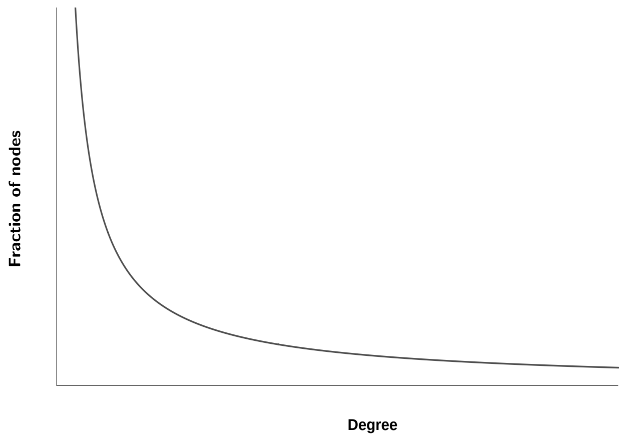


Figure 3.2: An example of the degree distribution observed in different types of networks. A large fraction of nodes has a low degree of centrality, while a few others concentrate a disproportionate number of connections.

The *global clustering coefficient* is another statistic used at the network level of analysis. This coefficient measures the extent to which the relationships in the network display transitivity. The clustering coefficient (cc) is defined as

$$cc = \frac{t_{\Delta}}{t_{<}}, \tag{3.6}$$

where t_{Δ} is the total number of closed triads (i.e., triangles) and $t_{<}$ is the number of open and closed triads. A coefficient near 1 suggests that relationships are transitive (e.g., accomplices of an offender are also accomplices), while those near 0 indicate the opposite; that accomplices of a particular node tend not to commit crimes together. The network presented in 3.1 has a relatively high coefficient of 0.6. In this network, the relationship between A, B, and C is transitive: A and B are connected, for example, through 3 shared criminal events, A and C, through a single event, as are B and C. However, the relationships between A-C-D and B-C-D are not transitive since D did not co-offend with A or B. The study in Chapter 5 explores the idea of transitivity in co-offending networks. It uses a different method to estimate clustering coefficients in networks modelling the interactions between offenders and criminal events.

By considering networks as a whole, it is possible to examine whether nodes connect to others with similar characteristics. These characteristics could include age, number of previous arrests, or income. *Assortativity mixing* measures the extent to which nodes connect to similar others (i.e., *homophily)* (Newman, 2018). Apart from non-network attributes of nodes, it is possible to estimate the tendency of nodes to connect to others with similar positions in the network, such as those with similar degree centrality (i.e., assortativity mixing by degree).

The example network shown in Figure 3.1 is a unimodal or one-mode network, meaning that the nodes are of a single type (i.e., belong to the same *mode* or class). In this network, all the nodes represent individuals. However, networks can include nodes belonging to multiple modes. *Bipartite* or two-mode networks, as their name indicates, are a particular type of network in which the nodes belong to two different modes, and edges can only exist between nodes from different modes. In sociology, these networks are suitable for studying patterns of affiliations between individuals and events, or between individuals and groups. The edges in bipartite networks behave differently to those in unimodal networks: they connect nodes of different types and do not connect pairs of nodes in the same mode.

Bipartite networks can model co-offending relationships by linking offenders to criminal events. Figure 3.3 represents an example of a network modelling the connections between five offenders (A-E) and the criminal activities in which they participated (1-5). In this example, co-offenders A and B co-executed three crimes; C co-executed 1 crime with A and B and another one with D. Similarly, D participated in one crime with C, and E executed alone crime '5'.

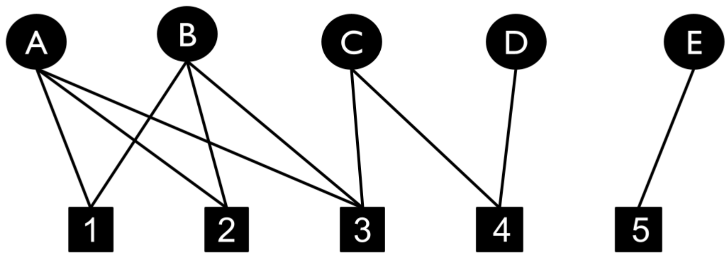


Figure 3.3: An example of a bipartite co-offending network with five nodes. Nodes A-E represent offenders and nodes 1-5 represent criminal investigations.

Since the edges in bipartite networks behave differently from those in one-mode networks, only some of the metrics and measures developed for one-mode networks can be used to analyse bipartite networks (Wasserman & Faust, 1994). For example, the degree centrality of a node in a bipartite network will provide different information depending on the reference mode. In a co-offending network, for example, the degree centrality of an offender will indicate the number of events in which the offender features. Alternatively, from the criminal investigation perspective, the degree centrality will indicate how extensive an investigation is in terms of the number of offenders under investigation.in each of these, two nodes are connected if they share a neighbour in the bipartite network

The methods used to analyse bipartite networks are less developed than those for one-mode networks. Consequently, researchers tend to transform bipartite networks into one-mode networks through a process known as *projection*. This process divides the original bipartite network into two one-mode networks: one for each mode. In each of these, two nodes are connected if they share a neighbour in the bipartite network. In a co-offending network, for example, one projected network would represent offenders and the other criminal investigations, and offenders would only share an edge in the one-mode projection if they were connected to the same investigation in the original bipartite network. Likewise, two criminal investigations would be connected if they share at least one offender. Projected networks can include weighted edges to represent the number of investigations shared by a pair of offenders.

The corresponding one-mode projection of the bipartite network presented in Figure 3.3 is the network presented above in Figure 3.1. In this example, the one-mode projection shows that A and B are connected through a weighted edge since they co-executed three crimes (1-3). Since C is also connected to A and B only through one criminal event (3), the edges connecting A, B, and C nodes have a weight of one. Furthermore, as no other person participated in crime ‘5’, E becomes an isolated node in the one-mode projection, indicating that it is a solo offender.

Once the projection of bipartite networks concludes, one-mode metrics can be used to analyse them from the three perspectives explained above (i.e., particular nodes, assemblies of nodes or the network as a whole). The study included in Chapter 6 uses one-mode projected networks to study the evolution of co-offending networks. In contrast, those included in Chapter 5 and 7 rely on the original bipartite network connecting offenders and criminal investigations.

One-mode projections are, in general, a union of multiple cliques (Newman, 2018). For example, a criminal investigation with four offenders will yield a clique in the projected network in which all four nodes share a link. Consequently, bipartite networks' projection creates more fully-connected cliques than prototypical one-mode networks. This characteristic of one-mode projections, in turn, biases some network statistics, including assortativity mixing by degree and clustering coefficients (Wasserman & Faust, 1994). For this reason, Chapter 5 introduces an alternative to address this bias when discussing clustering coefficients in co-offending networks.

3.3 Summary

This Chapter aimed to introduce the reader to the network-related concepts used in this thesis. An exhaustive presentation of this topic was not intended, as there are reviews elsewhere that cover this material comprehensively (e.g., Newman, 2018; Barabási, 2016). There are wide-ranging reviews tailored for those interested in networked criminology. For example, the research guide recently published by Bichler (2019) has become a go-to reference for those working in this field. However, this research guide omitted a discussion about bipartite networks and how they can provide valuable insights. As mentioned in Chapter 1, this thesis aimed to start filling this gap by showing the information that bipartite networks can convey when studying co-offending.

Chapter 4

Data: Using Information About Criminal Investigations to Study Co-offending

4.1 Overview

This Chapter describes the data used in the three studies presented in Chapters 5 - 7. It also discusses the limitations of using official records to study co-offending and presents some descriptive statistics to show the extent of this phenomenon in Colombia's capital city, Bogotá.

4.2 Data

The data used in this thesis was obtained from the Colombian Attorney General's Office (AGO), the authority in charge of investigating crimes and prosecuting offenders before the Courts of Law in Colombia. It contained information about offenders ($N = 274,689$) linked to criminal investigations ($N = 286,591$) in Colombia's capital, Bogotá - a city with more than nine million inhabitants. Specifically, the data included information about adult co-offenders (18 years old or older) associated with investigations that started between 01/01/2005 and 31/12/2018. These investigations were related to all crime types included in the Criminal Code (Law 599/2000) in which (i) Courts of Law reached a guilty verdict, (ii) those on trial as of December 2019, (iii) those in which offenders pleaded guilty, and (iv) cases that exceeded the time the Criminal Procedural Law granted to reach a verdict. The latter were included since defendants often try to prolong the length of trials in order to exceed the limit granted by the Law. Once trials exceed this limit, the judges must declare an investigation closed, avoiding a final decision. Due to the prevalence of this malpractice, this study included these investigations.

The Colombian Criminal Code classifies offenders into two broad categories: *authors* and *participants*. The first category consists of those who execute the criminal act (chief actors), and the second, individuals who had an essential role before or after the execution of the criminal act (e.g., accessories or those who encourage the commission of a crime without participating in it). The data used here included both categories; consequently, it aligns with Tremblay's (1993) definition of co-offenders. He defined co-offenders as all those with a relevant role before, during, or after the execution of a crime (Tremblay, 1993).

Each observation in the data set consisted of a single offender related to a specific criminal investigation. The encrypted national identity number (NIN) was used to identify each offender. Criminal investigations, in turn, were distinguished through the Criminal Investigation Record Number (CIRN), a code used by the AGO to identify each investigation.

According to the Criminal Procedural Rules (Law 906/2004), the

AGO should prosecute two or more individuals under the same investigation in two scenarios. First, when there is evidence of a criminal partnership between offenders; that is, if two individuals have co-offended, the AGO must investigate them under a single investigation. Second, when crimes share the same *modus operandi*, there is a close relationship between the crimes committed in terms of time and space, and the evidence produced in one case is relevant for the other. Based on this legal precept, co-offending relationships were inferred when two or more offenders were involved in the same criminal investigation (i.e., two or more offenders were associated with the same CIRN).

Each observation in this data set linked one offender (NIN) to a criminal investigation (CIRN). If the AGO prosecuted two offenders under the same investigation, there would be two observations: one for each NIN, and both would have the same CIRN. Likewise, if offenders were related to multiple investigations, there would be one observation for each combination of the NIN and the multiple CIRNs. If a specific NIN-CIRN pair occurred more than once (i.e., an individual is associated multiple times with the same crime), the duplicates were ignored.

The CIRNs had a timestamp corresponding to the start of the investigation. Some of these dates matched the day when offenders committed the crime (e.g., investigations triggered by an arrest *in flagrante delicto*), but others did not. For example, when victims reported a crime several days (or even months) after its commission, the date attached to the CIRN would not match that in which the crime was committed. It was impossible to differentiate between these two scenarios; therefore, it was assumed that the dates attached to each CIRN corresponded to those on which offenders committed the crimes.

The study presented in Chapter 6 relied on these timestamps to study the evolution of the three co-offending networks.

Based on how the data was retrieved, there is a self-imposed boundary in the networks presented in Chapters 5 - 7 - i.e., it only captures information about those offenders who came to AGO's attention in this city between 2005 and 2018. Moreover, the data relates to criminal investigations of crimes committed in Bogotá; hence, it was not possible to establish if the individuals in the network may have had additional collaborators associated with crimes executed in other cities.

As highlighted in the following chapters, a refined analysis of co-offending in general, and accomplice selection and criminal specialisation in particular, could not be achieved as offenders' socio-demographic information was missing (e.g., ethnicity, number of arrests before 2005, specific age, or employment status). The AGO does not record this information, and recording it would have implied extracting information *in situ* of more than 200,000 criminal investigations held in physical archives throughout the city.

At least four limitations derive from using the data retrieved from the AGO. The first of these relates to completeness. Co-offending, like other crime-related activities, has 'dark' figures; that is, a proportion of events that do not appear in official records. For multiple reasons, an accurate number of the offences committed, and the individuals involved in them, is unattainable. For example, victims might fail to report the crimes they suffer or identify the participation of additional accomplices. Law enforcement agencies (LEAs) might also fail to record the crimes once the victims have decided to come forward (Carrington, 2014). Moreover, once reported, prosecutors might be unable to establish the identity of all those who participated in the criminal event, forcing them to close an investigation. Accordingly, the AGO's records do not reflect the universe of crimes committed in this city during this particular time frame. In turn, this means that data used in this thesis also will not include the universe of offenders and their co-offending relationships.

The second limitation arises from the nature of legal proceedings. The data set included records of those who were on trial at the time the data was retrieved from the AGO. Prior to starting a trial, prosecutors must have some certainty about the defendants' guilt. It is possible, however, for a Court of Law to acquit a defendant if prosecutors fail to prove the link between the crime and the defendant. In this case, the data set would include information about offenders who were later found not guilty. The data set could also include information about wrongful convictions, i.e., innocent people convicted by a court of law. Thus, the data may contain information about people who were either wrongfully convicted or never convicted.

Data processing errors created a third limitation. To observe data protection regulations, the AGO used the MD5 algorithm to encrypt offenders' national identity numbers (NINs), and this returned errors for either missing values or NINs that included special characters or blank spaces. About 12.7% (51,668) of the observations yielded an error during this process. Without the original numbers, it was impossible to run a node disambiguation process (Newman, 2018) to know the exact number of unique individuals represented in the observations that yielded an error. The observations that yielded an error during the encryption process were excluded from the analysis.

The fourth limitation is related to the biases introduced by modifications in organisational practices. Changes in police practices, data recording procedures, resource constraints, and law enforcement agencies selectiveness are among the issues that can affect data's reliability and validity, particularly over time (Campana & Varese, 2020). Grasping these modifications might be challenging and sits outside the scope of this research. However, some precautions were taken to minimise risks. The data represents a *complete extraction* of the investigations that had completed at least an initial stage in which the AGO gathered information about those deemed responsible. It also covers fourteen years' worth of data, allowing for organisational variations to be included.

The starting period of this study period was chosen deliberately. In 2005, an adversarial criminal justice system was introduced in this city, changing the AGO's functions and how they recorded data. By considering only information under the new system, it was possible to minimise the risk of including data recorded through different organisational procedures. The endpoint coincided with the starting date of the PhD programme. Moreover, the data extraction was not limited to a set of specific crimes, so it included all the crime types prosecuted within this time frame. Accordingly, the data contained the outputs of multiple task groups of prosecutors and police units investigating and prosecuting offenders, and not those of a single working group.

Despite these limitations, the data provided by the AGO offered two advantages compared to traditional sources of information used in studies of co-offending networks. Apart from some contributions that used court records (e.g., Breckinridge & Abbott, 1912; Shaw & McKay, 1931; Reiss & Farrington, 1991), research in this field has mainly relied on arrest records held by police departments and, to a lesser extent, on victims' and self-reports Carrington (2014). Due to the configuration of Colombia's criminal justice system, the AGO's data resembles a unique combination of arrest and court records. Once the National Police arrests an individual, they liaise with prosecutors for them to appear before a Court of Law to verify that the Police followed due process and to formally initiate an investigation to collect evidence and accuse the offenders at a later stage. This initial stage requires the AGO to create a CIRN. Therefore, every person arrested will have, in principle, a CIRN linked to its NIN. By selecting active CIRNs, the AGO's data resembled arrest records (i.e., people who were arrested and are under trial). On the other hand, the AGO's data is similar to court records because it includes information about criminal investigations in which offenders pleaded guilty and those in which a Court of Law found offenders responsible for the crimes the AGO prosecutes.

The information included in this data set contains the outcomes of (lengthy) criminal investigations in which prosecutors tried to identify all those who participated in a criminal event. This data had updated information on the results of investigations in which prosecutors could have added new offenders to ongoing investigations. In this respect, the data set included co-offending relationships that could not be seen by only considering instances in which co-offenders were co-arrested. When using arrest records, researchers establish a co-offending relationship based on cases in which the police arrested two or more offenders simultaneously. By restricting co-offending relationships to co-arrests, it is impossible to identify actual co-offending relationships of individuals detained at different points in time, an obstacle that it is possible to surmount to some extent with the data used here.

Despite the official records' shortcomings, this source of information offers researchers an option for studying co-offending relationships at a large scale. It also contains the information to study this phenomenon from a network perspective. While AGO's data are limited in some ways, it provides unique insights into co-offending networks in large cities, such as Bogotá.

4.3 Descriptive statistics

The data used in this study contains information on 274,689 unique offenders and 286,591 criminal investigations that started between 1/1/2005 and 31/12/2018. Only 15% of the investigations (n = 43,506) included two or more offenders, and they included 33.6% of the offenders included in this study (n = 98,888). When partitioning the data in one-year intervals, the proportion of offenders who participated in at least one co-offence'= (i.e., participation rates) ranged between 26 and 37% (see Table 4.1), which are similar to those reported by Carrington (2014). Note that those reported by Carrington (2014) derived from studies using information from Canada, Sweden, the UK, and the USA, most of which were related to juvenile offenders. The rates reported here correspond to adult co-offenders. Accordingly, they suggest that co-offending is a trait also shared by adult offenders in this city.

Table 4.1: Descriptive statistics of the data set used to study co-offending in Bogotá, Colombia (2005-2018). (a) Number of offenders, (b) number of co-offenders, (c) proportion of co-offenders, (d) number of investigations, (e) number of investigations related to co-offences, (f) proportion of investigations related to co-offences, (g) average number of offenders per investigations related to co-offences, (h) average number of investigations per co-offender.

Year	**(a) Off.**	**(b) Co-off.**	**(c) Prop. Co-off.**	**(d) Inv.**	**(e) Co-off. Inv.**	**(f) Prop. Inv. Co-off.**	**(g) Av. off per Inv.**	**(h) Av. inv per off**
2005	16,612	5,173	31.1	14,532	2,248	15.5	2.5	1.3
2006	18,910	5,820	30.8	16,803	2,574	15.3	2.5	1.4
2007	23,088	7,014	30.4	20,405	3,080	15.1	2.4	1.3
2008	21,576	5,760	26.7	19,379	2,460	12.7	2.5	1.3
2009	30,428	8,363	27.5	27,644	3,707	13.4	2.4	1.3
2010	30,612	9,043	29.5	27,680	3,991	14.4	2.4	1.3
2011	28,895	8,842	30.6	25,911	3,858	14.9	2.4	1.3
2012	27,257	8,255	30.3	24,250	3,536	14.6	2.4	1.3
2013	23,386	7,721	33.0	20,404	3,177	15.6	2.5	1.4
2014	21,897	7,969	36.4	18,827	3,266	17.4	2.5	1.4
2015	22,777	7,747	34	19,945	3,171	15.9	2.5	1.4
2016	22,905	8,284	36.2	19,689	3,272	16.6	2.7	1.5
2017	21,368	7,528	35.2	18,504	2,928	15.8	2.7	1.4
2018	15,460	5,789	37.4	12,618	2,238	17.7	2.7	1.4

The figures included in Table 4.1 also reveal an increase in the proportion of co-offenders (column c), the proportion of investigations related to co-offences (column f), and the average number of offenders in investigations about co-offences (column g) from 2011 up to 2018. The proportion of co-offenders went from 30.6 in 2011 to 37.4 in 2018, with a two percentage point drop in 2015. Similarly, the number of co-offenders per investigation went from 2.4 in 2012 to 2.7 three years later. Determining the specific causes of these variations sits outside the scope of this thesis. However, multiple factors could explain them. For example, a hypothesis that future research could evaluate is that co-offending participation rates are susceptible to changes that affect how criminal investigations are conducted (e.g., the allocation of investigators per investigation or the creation of incentives for offenders to cooperate) (Campana & Varese, 2020).

According to this data, co-offences were committed, on average, by two offenders. This figure is consistent with the prior findings about co-offending groups' size presented in Chapter 2. It is also consistent with the findings presented in Chapter 6 that uses a networked approach to identify co-offending groups in bipartite networks.

Table 4.2 presents the distribution of crime types linked to co-offending investigations per year. The grouping strategy of crimes follows the classification used by Colombian Criminal Law. In this Law, criminal offences are classified based on the legal rights they intend to protect. For example, eight crime types protect a person's life and integrity; this category includes genocide, homicide, abortion, and assault. Crimes such as arms trafficking and trafficking of firearms restricted for military use fall within the public safety category. Those affecting the legitimacy of legal procedures, such as bribery, corruption, or fraud, are included in crimes against public administration and forgery or falsification of public documents in crimes against public trust. This classification is a natural one to apply for crime in Bogotá, particularly given the lack of consensus about how to group crimes when studying, for example, criminal specialisation (Mazerolle, Brame, Paternoster, Piquero, & Dean, 2000; Sullivan, McGloin, Pratt, & Piquero, 2006). The study presented in Chapter 7 uses this classification to study the criminal specialisation of co-offending groups.

Crimes against private property were prevalent throughout the study period, and accounted for the largest proportion of co-offending investigations. The proportion of investigations that have included such crimes is consistent with the previous studies presented in Chapter 2. Burglaries, robberies, thefts of cars, and minor thefts are usually associated with co-offending since they often require some level of collaboration between the offenders (Carrington, 2014; van Mastrigt & Farrington, 2009; van Mastrigt, 2017; van Mastrigt & Carrington, 2019). The prevalence of crimes against life and personal integrity and public safety (arms trafficking) might also be related to the findings reported in Chapter 2 about the increased likelihood of co-offenders using firearms and injuring their victims (Carrington, 2002; Alarid et al., 2009; Lantz, 2018).

4.4 Summary

This Chapter described the nature of the data used to complete the studies presented in Chapter 5-7. It described how the information recorded by the AGO combined two sources of information - arrest records and court files - that are generally not combined when studying co-offending. Limitations derived from the nature of this data

Table 4.2: The top 5 crimes linked to co-offending investigations. The number in brackets indicates the proportion of investigations that included each crime. For example, in 2005, 40 per cent of the investigations linked to co-offences included a crime against private property. Prop = property, LPI = Life and personal integrity, PS = Public Safety, PA = Public Administration, PH = Public health, PT = Public Trust

Year	Top 1	Top 2	Top 3	Top 4	Top 5
2005	Prop (40%)	LPI (26%)	PS (12%)	PA (6%)	PT (6%)
2006	Prop (35%)	LPI (27%)	PS (11%)	PA (8%)	PT (7%)
2007	Prop (35%)	LPI (29%)	PS (9%)	PT (7%)	PA (7%)
2008	Prop (36%)	LPI (22%)	PS (10%)	PT (7%)	PA (6%)
2009	Prop (36%)	LPI (30%)	PS (8%)	PH (6%)	PA (5%)
2010	Prop (38%)	LPI (31%)	PS (7%)	PH (6%)	PA (4%)
2011	Prop (38%)	LPI (31%)	PH (7%)	PS (7%)	PA (6%)
2012	Prop (38%)	LPI (35%)	PS (7%)	PA (6%)	PH (5%)
2013	Prop (40%)	LPI (33%)	PS (7%)	PA (6%)	PH (5%)
2014	Prop (42%)	LPI (32%)	PS (8%)	PH (6%)	PA (5%)
2015	Prop (41%)	LPI (30%)	PS (10%)	PH (5%)	PA (5%)
2016	Prop (42%)	LPI (26%)	PS (11%)	PH (5%)	PA (5%)
2017	Prop (39%)	LPI (23%)	PS (13%)	PA (7%)	PH (6%)
2018	Prop (38%)	LPI (29%)	PS (12%)	PH (5%)	PA (5%)

were also addressed. It was argued that, despite these limitations, the official records used here are among the few sources of information that can be used to study co-offending relationships of more than 90,000 offenders in a 14-year window.

The reader will note that Chapters 5, 6, and 7 include a subsection describing the data used for each particular study because there were some variations amongst them. For example, Chapter 5 used information about all the co-offence investigations, but the study in Chapter 7 used a portion of the data due to computational limitations.

Chapter 5

Triadic Closure in Co-offending Relationships

5.1 Overview

This Chapter explores triadic closure in co-offending networks -i.e., the tendency of two individuals to co-offend if they share an accomplice- using a method that addresses the risk of overestimating clustering coefficients when using one-mode projections. It also assesses the statistical significance of clustering coefficients using null models. The observed coefficients range between 0.05 and 0.53 and are statistically significant, indicating that accomplices become sources of information about potential associates. They support the idea of preventing crime by targeting offenders' trustworthiness and disrupting information flows.

5.2 Introduction

While individuals acting alone commit numerous crimes, many others involve two or more offenders acting together. These range from pairs of friends shoplifting to large organised groups engaged in transnational illegal activities. Moreover, in many cases, the collaborative aspect is integral to the crime, in the sense that it would not occur without the contributions of all actors (Tremblay, 1993). Therefore, understanding the characteristics of such co-offending can improve the understanding of criminal behaviour and inform prevention efforts.

How offenders come to collaborate is one of the aspects that can inform prevention, and it has been subject to multiple theoretical perspectives as discussed in Chapter 2 (for a review, see van Mastrigt, 2017). Such collaborations may be a function of circumstance: individuals encounter others in their milieu who may be amenable to crime and opportunistically decide to offend together. Others, however, emphasise a more rational process in which individuals choose to co-offend with those accomplices who are likely to maximise the benefits and reduce the costs of the prospective crime. This process involves identifying potential accomplices based on their competence and trustworthiness.

Network analysis is an approach that has considerable potential to shed light on these issues (see Chapter 3). In an immediate sense, offenders' social contacts constitute a supply of potential accomplices and are likely to reflect their wider social environment. Furthermore, networks are a source of information about others' skills and reputation: for example, offenders may vouch for each other's trustworthiness and provide introductions. Bichler (2019) recently proposed an integrated framework, referred to as a 'theory of networked opportunity', to understand how social networks shape the interactions between offenders and their surroundings that are conducive to opportunities for crime (Felson & Clarke, 1998). Concerning personal networks, the framework suggests that the information and resources available to individuals through their social networks affect their perceptions and decisions to engage in criminal activity (Bichler, 2019, p. 84).

Analysing networks linking offenders based on their criminal co-participation can shed light on how individuals select their accomplices. Triadic closure is one feature of co-offending networks that the literature has not thoroughly explored and could explain how offenders find and select their accomplices. It refers to the tendency for two individuals to be connected if they share a common contact (Wasserman & Faust, 1994). In the context of co-offending, this corresponds to an increased probability for two individuals to co-offend if there is a third individual with whom they have also co-offended. Such a tendency should be anticipated if social networks mediate the accomplice selection, with the 'third' actor either providing the introduction or assuring trustworthiness.

Accordingly, the study presented in this paper aimed to adequately measure the extent to which co-offending networks display triadic closure by examining the co-offending behaviour of offenders in Colombia's capital city, Bogotá, between 2005 and 2018. Co-offending networks were built using the records of criminal investigations relating to a wide range of crime types to quantify the presence of triadic closure. As discussed in Chapter 2, the focus on Colombia, a middle-income country with specific crime problems, complements existing literature on this topic that primarily focuses on high-income countries in Europe and North America.

This study also contributed to the literature by addressing a potential bias in previous studies. In technical terms, co-offending networks are the one-mode projections of bipartite networks linking offenders to crime events. As such, they typically contain many fully connected cliques, corresponding to instances where multiple actors have participated in the same crime. While these cliques include multiple connected triads, many do not reflect closure in a *meaningful sense* since they do not correspond to separate co-offending decisions. Existing studies of co-offending networks do not account for this, simply treating the one-mode projection as a stand-alone network. The consequence is that clustering may be over-estimated. The analysis presented here relied on an approach developed by Opsahl (2013) to address this issue by adjusting for the bipartite nature of the underlying data.

5.3 Background

As discussed in Chapter 2, while co-offending behaviour has been documented empirically in many studies, there has been little theoretical development concerning the mechanisms by which such collaborations come about (Weerman, 2014). Nevertheless, general principles have been proposed to explain accomplice selection across various contexts. This section outlines these theoretical perspectives introduced in Chapter 2 to argue that they imply that co-offending networks are expected to exhibit some degree of triadic closure.

5.3.1 Accomplice Selection

The few theories that explain accomplice selection lay along a continuum. At one end, accomplice selection describes a spontaneous process arising from immediate circumstances. In this model, willing offenders continuously signalled their readiness to offend (Reiss, 1988; Alarid et al., 2009); when a criminal opportunity arises, sufficiently motivated offenders might decide to collaborate to take advantage of it, even without sharing a previous relationship. These spontaneous, improvised decisions will lack a detailed plan and a thorough assessment of the risks and benefits of the co-execution of crime.

At the other end of the continuum, accomplice selection is hypothesised to be a rational process in which offenders decide to co-offend with those accomplices that could maximise benefits and reduce costs (Tremblay, 1993; Weerman, 2003). In doing so, offenders evaluate potential partners based on their perceived trustworthiness and ability to help maximise the expected rewards of the criminal venture (Tremblay, 1993). This evaluation involves judging accomplices' criminal capital (Hochstetler, 2014).

The relative contributions of these processes - in particular, the extent to which a choice is rational - will vary according to context (e.g. crime type). Regardless of the precise mechanism, however, the decision to co-offend and the selection of accomplices involve two key considerations: how individuals become aware of potential partners and how they evaluate such partners' value as potential co-offenders. The first determines the 'pool' of prospective accomplices, while the second reflects their relative merits.

Most immediately, offenders are likely to encounter potential accomplices through their immediate social and physical environment. Individuals' social networks provide a source of potential co-offenders, either through immediate contacts or friends-of-friends (McCarthy et al., 1998). Furthermore, these pre-existing relationships - and the information circulating within the broader social networks - are likely to provide insight into the trustworthiness, criminal capital, and reputation of potential partners (McCarthy et al., 1998). In turn, these relationships allow offenders to make informed judgements to reduce the inherent risks of co-offending. Consistent with this, research has found that siblings, friends, acquaintances, and work colleagues tend to co-offend more than groups of strangers (Sharp et al., 2006; Reiss & Farrington, 1991).

Beyond, but related to, their social networks, people's immediate geography also bounds the search for potential accomplices (van Mastrigt, 2017). Most directly, proximity gives rise to opportunistic interactions: motivated offenders are likely to make contact with and communicate their intentions to potential partners located nearby (Reiss & Farrington, 1991). More generally, though, the interactions and relationships that might lead to collaboration are also likely to be shaped by offenders' *activity spaces*; the places in which individuals tend to move for work, leisure, and other routine activities (Brantingham et al., 2017). Thus, individuals are more likely to co-offend with those who coincide in these spaces simply because of the increased availability and potential for interaction.

As a typical example, criminal collaboration can also arise from the confluence of motivated offenders in informal settings known as *offender convergence settings* (Felson, 2003). In these settings, which typically have reputations as hubs of criminality, motivated offenders interact through unstructured activities with potential accomplices and select those available to seize a criminal opportunity. Accordingly, co-offending relies on the convergence of potential co-offenders in informal settings, the interaction between them, and a minimum amount of time to socialise, select one another, and share information or other resources relevant to executing a crime.

Having encountered, or become aware of, potential accomplices via these mechanisms, offenders will judge their suitability for participating in crime. As mentioned, these judgements will consider various factors, including the capacity to commit the crime and the likelihood of successful collaboration. The first of these may involve preferences for specific characteristics, whether inherent (e.g. age, sex or background) or related to their criminal capital (i.e. experience and aptitude in criminal activity), which may mean that specific candidates from the available pool are preferred over others.

On the other hand, a fundamental issue in the evaluation of potential partners is trust (Tremblay, 1993). Trust corresponds to the likelihood that a collaborator can be relied upon to fulfil their role and not betray their co-offenders. Motivated offenders assess accomplices' trustworthiness before selecting them, typically by drawing on information accessed through personal contacts. Because of this, individuals rely on their trustworthiness to create and protect a reputation for future criminal ventures. Hence, their reputations, built upon their behaviour in previous experiences, can also be considered part of their criminal capital.

5.3.2 Triadic closure in co-offending networks

The mechanisms outlined in the previous section imply that the formation of co-offending relationships is subject to several tendencies and dependencies. In turn, these will be expected to be manifested in co-offending networks through structural regularities. While several such regularities might be anticipated, one in particular - *triadic closure* - arises consistently as a logical consequence of these mechanisms. This property became the primary focus of this analysis.

Triadic closure refers to the increased tendency of two individuals to make a direct connection if they share a common neighbour (Wasserman & Faust, 1994). This concept echoes transitivity in interpersonal relationships: if A is friends with both B and C, then it is likely that B and C end up being friends (Holland & Leinhardt, 1971).

Figure 5.1 illustrates the concept of triadic closure by presenting a network comprised of three individuals (A, B, and C), referred to as a *triad*. The solid lines between A-B and A-C represent existing relationships (e.g. friendship or prior co-offending). Since B and C share a common neighbour, triadic closure predicts that these two individuals will likely develop a direct connection (dashed line).

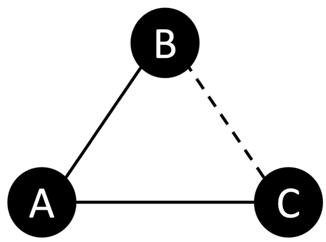


Figure 5.1: Example of triadic closure in social networks. The solid lines represent relationships between A-B and A-C. B and C are likely to be connected (dashed line) since they share a connection to a common individual, A.

The accomplice selection theories proposed so far neither rule out nor explicitly endorse the existence of transitivity in co-offending relationships since they tend to omit a discussion about accomplices' role in procuring potential accomplices for future crimes. Despite this, the proposed mechanisms share three elements with theories explaining triadic closure more generally. These elements are trust, the limitations posed by geographic locations, and homophily. Based on these commonalities, it is expected to see this trait in co-offending networks.

Trust, or the commitment to a relationship without knowing how the other person or group of persons will behave (Burt, 2005), is a critical element to explain why social networks display triadic closure. Two individuals sharing a connection to the same person will have a basis to trust one another and, therefore, will be more likely to create a direct connection themselves (Easley & Kleinberg, 2010). Trust between two strangers sharing a common friend emerges from the possibility of using informal sanctions to discipline either person if they break social norms (Coleman, 1988). For example, if C fails to observe an expected behaviour towards B, the latter can gossip about C to A. Here, A acts as an intermediary between the other two. Since informal sanctions can harm individuals' reputations, all three are incentivised to observe social norms. Likewise, two actors can discipline a third for not complying with these norms (Wolff, 1950). In turn, the incentive for observing social norms reinforces trust among those who share a social connection (Coleman, 1988).

As explained in the previous section, trust plays a vital role in explaining accomplice selection (Tremblay, 1993). Few theories directly address the sources of information used by motivated offenders to evaluate the trustworthiness of potential accomplices, except for general references to the information circulating in offenders' social networks (McCarthy et al., 1998) or the 'underworld grapevine system' (Thrasher, 1963). However, as explained by von Lampe and Johansen (2004), previous accomplices can become a direct source of information about potential accomplices, their trustworthiness, and their criminal capital or reputation. This implies that previous accomplices can act as brokers, making contacts between unconnected individuals and potentially gaining some benefits in doing so (Burt, 2005; Morselli & Roy, 2008). Furthermore, this shared accomplice can arbitrate between them if one breaks a social norm (e.g., splitting the shares of a crime unevenly). In these ways, trust-based mechanisms can lead to transitivity in co-offending networks.

Regarding the limitation posed by geographical locations, Feld (1981)'s *focus theory approach* suggests that certain elements in the environment act as *social foci*. Social foci are 'social, psychological, legal, or physical entit[ies] around which joint activities are organised (e.g., workplaces, voluntary organisations, hangouts, families)' (p. 1016). According to this theory, individuals who share a social focus are more likely to create a mutual positive sentiment than those who do not share one. This can lead to triadic closure since two individuals sharing a connection to a third one might imply that they share one or more social foci: if so, the three will be likely to share a positive sentiment, and the triad will be likely to be closed.

Feld's social foci resemble the *offender convergence settings* suggested by Felson (2003) as drivers of co-offending. If these locations play host to unstructured interactions between potential offenders, then it is to be expected that some co-offending relationships may be formed. As per Feld's argument, these will be expected to result in tightly-connected structures exhibiting triadic closure.

Lastly, homophily - the tendency people have to associate with those who appear to be similar to themselves (McPherson et al., 2001) - is both a feature of accomplice selection processes and a potential explanation for triadic closure in social networks. Triadic closure is a byproduct of homophily (Granovetter, 1973) because sharing characteristics is transitive. If A is similar to B and C, then B and C must be similar. Accordingly, any network that displays homophily will likely exhibit some triadic closure.

Co-offending relationships are likely homophilic due to a combination of explicit preferences and structural opportunities, in line with the decision processes mentioned in the previous section (Van Mastrigt

& Carrington, 2014). Offenders may exhibit preference when they actively collaborate with similar others to validate their social status or identity or because shared characteristics can facilitate more accessible communication and cooperation, demanding less energy in these relationships. Consistent with this, co-offending group members tend to be homogeneous regarding their age, sex, ethnicity, or criminal experience (Weerman, 2003). Homophilic relationships may also arise due to the underlying distribution of social characteristics rather than as the result of a conscious process (Van Mastrigt & Carrington, 2014). For instance, if males are over-represented in the population of offenders, then it is more likely that two males will co-offend. When derived in this way, homophily in co-offending relationships is not a matter of individual choices but the opportunities posed by the underlying distribution of social characteristics.

Personal preferences, psychological biases, and structural opportunities create homophilic relationships between co-offenders. Since homophily implies that social networks will exhibit triadic closure, this trait is expected to be observed in co-offending networks.

As shown, trust, geographical limitations and homophily - three prominent hypothesised mechanisms for accomplice selection - all imply the existence of triadic closure; hence, this property should be observed in co-offending networks. Therefore, triadic closure became the focus of this paper: discussions on how it can be measured accurately for co-offending networks and whether it is present in a real-world network are included below. In doing so, no support for any particular one of the mechanisms discussed above was sought; they only tried to establish whether this anticipated feature was present.

5.3.3 Measuring triadic closure in co-offending networks

A co-offending network models the involvement of offenders in shared criminal activities. The nodes in these networks represent individuals. The lines (or edges) connecting them represent shared criminal events; each link indicates that the two offenders have collaborated in at least one crime. Following the example presented in Figure 5.1, A, B, and C would represent a set of offenders, while the solid lines represent crimes co-executed by each pair (A-B and A-C).

Co-offending networks are qualitatively different from other networks used to model the interactions between those participating in criminal activities. The information contained in court documents or arrest records about the co-execution of crimes by two or more individuals determines the presence of links in co-offending networks (i.e., who co-offends with whom). In contrast, research on organised crime groups has tended to examine communication networks (i.e., who speaks with whom) to model the interactions between individuals participating in organised crime-related activities (e.g., Morselli, 2009; Campana, 2011; Malm & Bichler, 2011). Hence, there is a difference between including individuals in networks based on the people they talk to and the contents of their conversation and creating connections between two or more individuals based on the joint execution of a crime - discussing criminal activities is not a crime in itself.

Clustering coefficients quantify the extent of triadic closure, or transitivity, in a network by comparing the relative proportions of closed (when the dashed line is present in the example mentioned above) and open (when it is absent) triads (Newman, 2018). The coefficient c is defined as

$$c = \frac{t_{\Delta}}{t_{<}}, \tag{5.1}$$

where t_Δ is the number of closed triads and $t_<$ is the total number of (open and closed) triads. A coefficient near 1 suggests that relationships are transitive (i.e., accomplices of an offender are also accomplices). One near 0 indicates that nodes with a common accomplice tend not to be connected themselves. Put differently: this coefficient represents the average probability of observing a connection between a pair of individuals who share a common accomplice (Newman, 2018).

So far, only two studies have reported clustering coefficients in co-offending networks. Iwanski and Frank (2013), using arrest records of individuals related to the illegal market of hard drugs in British Columbia (Canada) between August 2001 and August 2006, analysed the second-largest component of their network, containing 393 co-offenders. They observed that the clustering coefficients in this component ranged between 0.75 and 1.0.

Bright, Whelan, and Morselli (2020), using arrest records of 102,261 adult offenders in Melbourne (Australia) between 2011 and 2015, also reported a high clustering coefficient: 0.88 for co-offenders related to violent crimes; 0.63 in co-offending networks related to property crimes; and 0.83 for offenders arrested for participating in illegal markets (e.g., drugs). Combining all the offenders, regardless of their crimes, into a single network also reported a relatively high coefficient, 0.65.

Charette and Papachristos (2017) did not report a clustering coefficient for the co-offending networks they were analysing. However, they used a different proxy to assess transitivity in co-offending relationships by counting the number of shared contacts between pairs of co-offenders. Using arrest records and victims' reports from a random sample of co-offenders (n=8,621) in Chicago between 2006 and 2013, they observed that, on average, a pair of co-offenders shared 12.1 contacts (SD = 26). They also found that the odds of creating a direct relation between two offenders increased with the number of contacts in common.

While studies of co-offending networks have offered important insights, the analytical strategies employed thus far may mean that the calculated measures do not necessarily reflect the underlying principles of interest, especially triadic closure. In particular, the fact that analysis of co-offending networks typically does not account for the nature of the data that shows the connections between offenders and criminal events and not directly between individuals can introduce a bias in the measurement of network properties, including clustering coefficients.

When this co-offending network was constructed based on the joint-participation in criminal events, an implicit first step was creating a bipartite (or two-mode) network representing links between offenders and crimes. Figure 5.2 (a) presents an example of such a bipartite network, in which offenders A-D link to a set of criminal events 1-4. The links indicate, for example, that A and B are both associated with criminal event 2; in other words, they co-offended in that particular incident.

Given this bipartite representation, a co-offending network can be derived by taking its *one-mode projection* (Newman, 2018; Wasserman & Faust, 1994). This projection involves retaining only one of the node sets (in this case, the offenders) and adding links between pairs of nodes if, and only if, they are connected to the same criminal event in the original bipartite network. For example, Figure 5.2(b) is the one-mode projection associated with the above example. Then, it is possible to examine the resulting one-mode network using standard metrics and measures like the clustering coefficient.

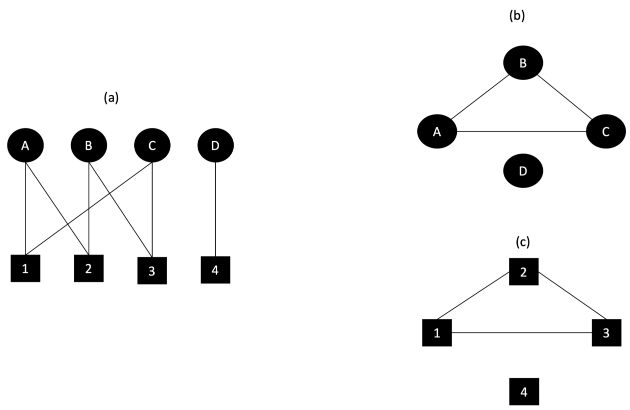


Figure 5.2: (a) Bipartite network with four nodes per mode and its two one-mode projections (b and c). Nodes connected to a common node in the original bipartite network will be connected in the one-mode projection.

As identified by Opsahl (2013), however, the projection of two-mode networks creates several issues for network analysis. In particular, the assumption that edges are independent - implicit in many approaches - is no longer the case for projected networks; instead, a single event (e.g. a crime) can simultaneously create multiple edges in a one-mode projection. More concretely, it is possible to consider one-mode projections as the union of multiple cliques (Newman, 2018), with each corresponding to a single node in the 'other' node-set in the original bipartite network. Thus, in co-offending, for example, each criminal event will generate a clique in the one-mode projection comprising all individuals who participated in the crime. Because of this prevalence of cliques, it is expected to observe networks derived by projection to have higher clustering coefficients than one-mode networks that were not induced through a projection process (Wasserman & Faust, 1994).

While this issue may not be problematic in technical terms, it has implications for interpreting clustering coefficients. The typical interpretation of clustering is that the 'closure' of the triangle structure results from an independent process that generated the original triad. In other words, the final link appears in the context of the two existing links already being present. This is not the case for projected networks: many closed triangles exist (within cliques) due to single events (i.e. co-participation in a single crime). From a theoretical point of view, this has quite different implications. For example, three individuals co-participating in a single offence does not reflect triadic closure in the same way as two individuals with an existing common accomplice choosing to co-offend together in a separate crime (see Figure 5.3). When the standard clustering coefficients are calculated for one-mode projections, this issue means they can substantially overestimate the level of triadic closure since many of the closed triangles identified may be due to single crimes.

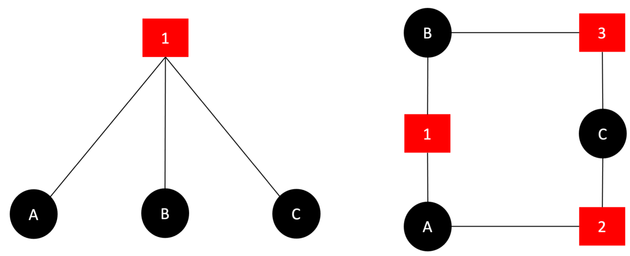


Figure 5.3: Two configurations of bipartite, co-offending networks:(a) three offenders (A-C) connected to a single investigation (1), and (b) three offenders (A-C) linked to three different investigations (1-3). Both components yield a closed triangle in the one-mode projection of offenders (A-C).

The two studies mentioned above used one-mode projections to calculate clustering coefficients. Iwanski and Frank (2013) connected two individuals arrested under the same criminal event identifier. Similarly, Bright et al. (2020) also matched offenders using 'event numbers': if two individuals shared the same event number, then they assumed they were co-offenders. Consequently, it is reasonable to conclude that the clustering coefficients reported in these studies may be subject to this issue. This issue may partly explain the high clustering values reported.

To avoid the bias introduced during the projection of bipartite networks, Opsahl (2013) proposed a modified approach to quantify clustering. The proposed approach measures closure among three nodes by referring to their configuration in the original bipartite networks. The approach involves examining paths of length four: in bipartite networks, these paths are analogous to those of length two used to estimate the coefficients in one-mode networks (see Chapter 3). Crucially, however, there is a distinction: while every 4-path in a two-mode network corresponds to a 2-path in its one-mode projection, not all 2-paths in a one-mode projection are created from 4-paths (the configuration in Figure 5.3 (a) is one such example). Thus, by reframing the calculation in terms of 4-paths in the original bipartite networks, it is possible to disregard triangles created by three or more nodes linked to a single investigation.

Opsahl's calculation involves examining whether each 4-path in the original bipartite network is *closed*: a closed 4-path is one where the two terminal nodes both have a common neighbour (i.e. the path is part of a 6-cycle). Figure 5.4 (a) contains an example to illustrate this approach. This network contains five 4-paths, three of which are closed.[1] These 4-paths each have a corresponding path of length two in the one-mode projection (Figure 5.4(b)).[2] Note, however, that the one-

[1] A-1-B-3-C (closed by 2); A-1-B-3-D; A-2-C-3-B (closed by 1); A-2-C-3-D; B-1-A-2-C (closed by 3).

[2] A-B-C (closed); A-B-D; A-C-B (closed); A-C-D; B-A-C (closed)

mode projection has three additional paths of length two - between nodes B, C, and D - since they are connected to the same event, '3'. Considering only those structures that correspond to 4-paths in the original two-mode network, such 2-paths - which are not triads in the same sense as the others - can be excluded from the calculation.

The modified clustering coefficient (C_{bn}) for bipartite networks is defined as

$$C_{bn} = \frac{\rho_c}{\rho}, \tag{5.2}$$

where ρ_c is the number of closed paths of length 4, and ρ is the total number of paths of length 4, both open and closed. As mentioned above, these 4-paths correspond to triads in the one-mode projection. Therefore, the coefficient measures the proportion of closed triads - while, crucially, omitting those created by three or more offenders linked to the same criminal event.

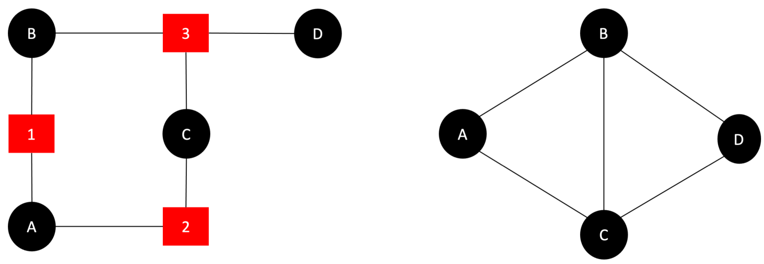


Figure 5.4: (a) Bipartite networks with four offenders (A-D) and three investigations (1-3). (b) One-mode projection of the bipartite network. The one-mode projection has additional paths of length two.

As well as the coefficient itself, Opsahl (2013) also shows how the calculated values can be compared to those expected under the null hypothesis that no tendency towards triadic closure is present (i.e.

connections are random). For each observed bipartite network, an ensemble of random networks is created by randomly rewiring its edges while preserving node degrees in both modes. The coefficient C_{bn} is then computed for each of these randomised networks, and these values form the null distribution against which the observed value can be compared. In this way, the statistical significance of the observed level of triadic closure can be estimated.

5.4 Data, analytical strategy, and results

This study used the data set described in Chapter 4. In short, this data contained information about criminal investigations carried out by the Attorney General's Office in Bogotá between 01/01/2005 and 31/12/2018 related to all seventeen categories of crimes included in the Criminal Code.

Each observation in the data set consisted of a single offender related to a specific criminal investigation. Therefore, the (encrypted) national identity number (NIN) was used to identify each offender and the Criminal Investigation Record Number (CIRN) to identify individual criminal investigations. The data was partitioned into twelve rolling-temporal windows of three years (2005-2007; 2006-2008; (...); 2016-2018). This window size provided a suitable number of data points (i.e., windows) with a reasonable overlap. The sensitivity analysis in Appendix A presents that the results only vary slightly with the value of this parameter.

The R package *igraph* (Csardi & Nepusz, 2006) provided the functionalities to create a bipartite network for each window. Table 5.1 presents the total number of offenders, the number of offenders who co-offended with at least one other, the total number of investigations, and the number of those that included more than one offender (i.e., co-offending investigations). As the networks yielded in each window were highly fragmented, this table also presents the number of components observed in each window.

Table 5.1: Number of offenders, co-offenders, investigations, investigations related to co-offenders, and components per window in Bogotá (2005-2018). MPI = multiperson investigations

Window	Offenders	Co-offenders	Investigations	MPI	Components
1	56,367	17,572	51,740	9,777	8,373
2	61,342	18,237	56,587	9,880	8,472
3	72,303	20,775	67,428	10,871	9,454
4	79,251	22,753	74,703	11,615	10,149
5	85,721	25,649	81,235	12,817	11,100
6	82,611	25,496	77,841	12,363	10,726
7	75,679	24,140	70,565	11,273	9,891
8	68,738	23,095	63,481	10,635	9,283
9	63,980	22,340	59,176	10,377	8,984
10	62,991	22,682	58,461	10,711	9,077
11	62,247	22,069	58,138	10,646	8,967
12	55,597	20,251	50,811	9,787	8,285

The clustering coefficients were calculated for these bipartite networks, as per the approach described in the previous section, using the R package *tnet* (Opsahl, 2009). Table 5.2 presents the clustering coefficients for the bipartite networks observed at each window, as well as the total number of paths of length four (closed) and the number of those that are closed (C_{bn} is the ratio of these). For comparison, this table also presents the standard clustering coefficients for the one-mode projections of these networks.

Several patterns were observed in the values of the modified clustering coefficient, C_{bn}. On the whole, the values of C_{bn} are substantially lower than their one-mode counterparts: while the latter are greater than 0.9 in all cases, the bipartite coefficients lie between 0.02 and 0.53. They are, however, greater than zero in all cases, indicating that triadic closure is nevertheless still present when measured in this form. In real terms, C_{bn} corresponds to the probability that

Table 5.2: Bipartite clustering coefficients, closed paths of length four, total paths of length four, and corresponding one-mode clustering coefficients

Window	Bipartite clustering coefficient (C_{bn})	Closed paths of length 4	Paths of length 4	One-mode clustering coefficient (C)
1	0.53	102,468	193,134	0.92
2	0.34	32,708	97,378	0.97
3	0.03	972	34,244	0.99
4	0.07	2,734	38,350	0.98
5	0.05	2,622	48,344	0.96
6	0.05	2,360	52,018	0.94
7	0.02	1,264	83,388	0.97
8	0.06	8,372	141,950	0.98
9	0.20	58,514	287,252	0.98
10	0.19	69,108	360,370	0.98
11	0.31	107,258	345,428	0.98
12	0.23	114,372	493,814	0.98

two accomplices of a randomly-selected offender will themselves have co-offended (on a different incident); in Window 1, for example, this value is 53%.

Notably, the values of C_{bn} fluctuate considerably across windows. The coefficient reached its highest value, 0.53, in 2005-2007 (Window 1), before dropping to 0.03 a couple of years later. It then remained low until 2011-2013 (Window 7) before rising again in later windows; by the final window, it reached 0.23. Other studies have reported temporal fluctuations in clustering coefficients (e.g., Amblard, Casteigts, Flocchini, Quattrociocchi, & Santoro, 2011) for other types of networks (e.g., co-authorship and citations). However, there are no reports of such behaviour in co-offending networks or for Opsahl's modified clustering coefficient.

It was worth examining the relationship between C_{bn} and other network features to find a possible explanation for these fluctuations. C_{bn} is negatively correlated with both the number of offenders who co-offended with at least one other ($r = -0.79$, $p < 0.05$) and the number of multi-person investigations ($r = -0.7$, $p < 0.05$), suggesting that additional investigations tend not to link those who already have an accomplice in common.

However, the pronounced fluctuation in the number of paths of length 4 in the networks was even more notable, which also mirrored that of C_{bn}. In real-world terms, each 4-path corresponds to an instance where an offender has co-offended with two others via two distinct offences, so there is wide variation in the prevalence of such cases. Some insight into this can be gained by examining the networks graphically: the plot in Figure 5.5 shows the largest connected component for two contrasting windows in bipartite form. Comparing the two diagrams, it can be seen that the participants in different events overlap much more in Window 12, where the number of 4-paths is very high. In Window 3, on the other hand, the component is dominated by a single event (which itself generates no 4-paths), with only minimal overlaps between events.

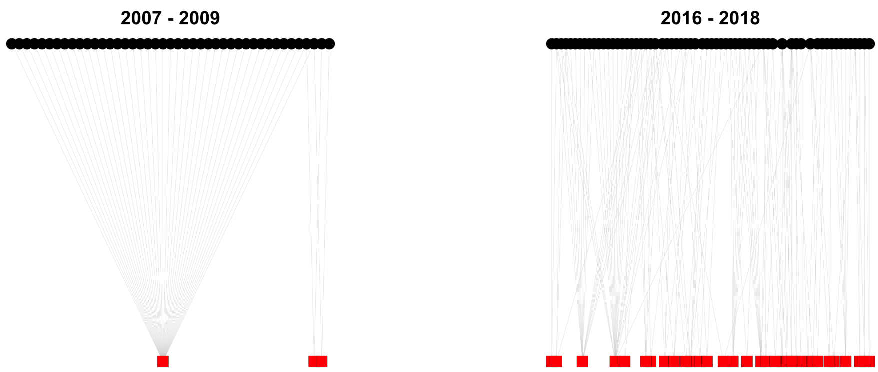


Figure 5.5: Bipartite plots of largest connected components: (left) Window 3, which contains 43 offenders and three events, and has 160 paths of length 4; and (right) Window 12, which contains 64 offenders and 33 events, and has 7974 paths of length 4.

This trend, which can also be observed in other windows, suggests that the variation in the prevalence of 4-paths is primarily a function of the extent to which distinct events share common participants. Overlaps between events - particularly when a large group of offenders is involved in multiple events - can quickly generate large numbers of 4-paths. This can also be expressed in terms of components: as more components merge (and therefore, the lower the number of components), the more 4-paths will be present. This also extends to the closure of 4-paths: the more individuals are involved in multiple crimes (and therefore 'bridge' components), the greater the chance that a 4-path will be closed. Indeed, C_{bn} is negatively correlated with the number of components ($r = -0.74$, $p < 0.05$). This appears to be the main source of fluctuation between windows.

This study is the first to report clustering coefficients using this modified approach, which considers the bipartite nature of co-offending networks. As noted above, there is a large discrepancy between these values and those obtained by applying the classic clustering coefficient to the one-mode projection: not only does the traditional coefficient indicate exceptionally high levels of triadic closure, but the fluctuation in values is not present. Both of these can be explained by the data set containing many investigations involving large numbers of offenders, which translate into large complete subgraphs (and, therefore, many closed triangles) in the one-mode projection. While these triangles dominate the calculation of the classic clustering coefficient, they are omitted from Opsahl's version because they do not correspond to 4-paths in the bipartite network. It is argued that, in this case, the modified coefficient gives a much more meaningful measure of 'genuine' triadic closure.

While the bipartite clustering coefficients are much lower than their one-mode equivalents, it is unattainable to state whether they represent significant levels of triadic closure. However, as explained in the previous section, it is possible to estimate their statistical significance by computing the expected distribution of these coefficients under a null model in which triadic closure is absent. If offenders sharing a common accomplice do not tend to co-offend together, this coefficient should be equal to 0 in the null model.

The null model used here consisted of 1,000 randomised simulations of each of the twelve bipartite networks. Each simulation included a randomly 'rewired' version of the original network that preserved the number of offenders and investigations and the number of connections each offender and investigation had. For each of the 12,000 simulated networks, the clustering coefficient was calculated using Opsahl's approach.

Table 5.3 presents the observed coefficients alongside the 97.5 percentile of the null model. In all cases, the 97.5 percentile values were exceptionally small (<0.001), likely reflecting the sparse nature of the underlying networks. Consequently, the observed values were at the extreme of the distributions under the null models, implying that they are significantly larger than those expected by chance. This suggests that, while lower than would be estimated using a one-mode projection, co-offending networks nevertheless show strong evidence that triadic closure plays a role in their formation. In the data, the probability for the accomplices of an accomplice to be subject to a different investigation was moderately high in the first two and last four windows and very low between 2007-2014. Between 2016 and 2018, for example, there was a 20% chance of randomly choosing a co-offender and observing a connection (i.e., a different criminal investigation) connecting two of their accomplices. While other values are lower than this, they are still much higher than expected without a triadic closure effect.

Table 5.3: Observed clustering coefficients and those at the 97.5 percentile in the distribution of the null models

Window	Observed C	97.5 Percentile
2005-07	0.53	<0.01e-04
2006-08	0.34	<0.01e-04
2007-09	0.03	<0.01e-04
2008-10	0.07	<0.01e-04
2009-11	0.05	<0.01e-04
2010-12	0.05	<0.01e-04
2011-13	0.02	<0.01e-04
2012-14	0.06	0.02e-04
2013-15	0.20	0.94e-04
2014-16	0.19	0.89e-04
2015-17	0.31	1.00e-04
2016-18	0.23	1.11e-04

5.5 Discussion

This Chapter was concerned with the extent to which co-offending networks - those in which links represent co-participation in criminal events - exhibit triadic closure. That this should be the case is predicted by some theories relating to criminal accomplice selection, which is the mechanism that drives link formation in such networks. This analysis sought to verify that triadic closure was indeed present in a co-offending network from Bogotá, Colombia, and to measure its extent rigorously. In doing so, it broadly addressed Bichler's (2019) *theory of networked opportunity* by examining the influence of social networks on offenders' decisions.

This study is the first to measure triadic closure in a set of relatively large co-offender networks using the original bipartite version of these networks. Unlike previous studies, the data used here combined information about cases that reached a guilty verdict or guilty plea with those in an early stage of the criminal investigation process. In addition, this data was related to the capital city of a middle-income country, Colombia, adding more evidence about co-offending in countries different from those previously considered in the study of co-offending (e.g., Canada, Sweden, the UK, and the USA). Moreover, the statistical significance of the clustering coefficients was assessed through a null model.

In the network under analysis, the probability of observing a co-offending relationship between the accomplices of an offender ranged from 3 to 53%. Thus, the results strongly suggest that social networks, especially those created through exposure to criminal events, exhibit a certain level of influence in the decisions made by offenders about whom to select as their accomplices.

One interesting feature of the findings is the high level of fluctuation observed in the bipartite clustering coefficient across windows. As noted above, this appears to be due to variation in the extent to which distinct criminal events share common participants (and, therefore, the extent to which components are linked). While there is a lack of certainty about the underlying reason for this variation, it is clear that some windows saw particular individuals associated with multiple offences to a greater degree than others, perhaps reflecting changes in enforcement or detection practices. Observing triadic closure depends on law enforcement agencies' ability to detect crime and reveal connections between known offenders. Assessing AGO's historical capacity and its impact on triadic closure in co-offending networks is beyond the scope of this thesis. However, future research could inform the direction and magnitude of the relationship between law enforcement's capability and the degree of transitivity observed in co-offending networks.

Even though time was included in the analysis of co-offending networks, the order in which offenders executed crimes was not considered: offenders could have committed these crimes simultaneously or sequentially. Despite this shortcoming, these findings suggest that some offenders could liaise in new criminal ventures with their accomplices' accomplices, despite having a relatively recent formal contact with the criminal justice system; the 'triangles' considered here were all formed entirely within 3-year windows. This fact suggests a reduced deterrent effect expected to operate when offenders increase their perceptions about the possibility of being apprehended and punished.

In methodological terms, the results highlight the importance of accounting for the bipartite nature of co-offending data when performing analysis. It was demonstrated that the typical approach of taking the one-mode projection and calculating standard clustering coefficients results in high (perhaps implausibly) values for transitivity being observed. The nature of co-offending data - relatively sparse, but with some crime events involving large numbers of offenders - means that many triangles result from single investigations. While meaningful, these triangles do not correspond to the theoretical meaning of triadic closure; it is assumed that links are formed independently. While the overall conclusion here is unchanged - there is still strong evidence of triadic closure - the value discrepancy suggests that the modified approach proposed by Opsahl (2013) generates accurate values.

Despite the novel features included here, this study faced the limitations discussed in Chapter 4. As mentioned, co-offending, like other crime-related statistics, has some 'dark figures' due to crimes not being reported by victims and law enforcement agencies failing to record them (Carrington, 2014). Moreover, while offenders on trial were likely to be responsible for the crimes prosecuted by the AGO,[3]

[3]Prosecutors need to have some level of certainty about offenders' responsibility

a court of Law could acquit some of the individuals included in the data set. The data may contain information about people who were not ultimately convicted.

Law enforcement should note the role co-offending networks have in co-offending. The question, therefore, is how these networks can be disrupted to prevent future crime. Felson (2003) suggested the intervention of co-offender convergence settings to prevent motivated offenders from finding accomplices. However, this is one of the multiple policy alternatives to reduce co-offending. First, it is necessary to understand the mechanisms driving triadic closure among offenders. For example, the existence of multiple convergence settings of offenders, trust and social norms between offenders, and the personal preferences or structural opportunities that allow homophilic relationships to emerge (or a combination of them) might explain triadic closure. Therefore, more research is needed to understand transitivity in co-offending relationships and the underlying mechanisms that result in the accomplices of an offender co-executing new crimes together.

before starting the trial.

Chapter 6

Studying the Evolution of Co-offending Networks

6.1 Overview

This Chapter aims to improve the understanding of criminal accomplice selection by studying the evolution of co-offending networks - i.e., networks that connect those who commit crimes together. To this end, four growth mechanisms (popularity, reinforcement, reciprocity, and triadic closure) were tested on three components observed in a network connecting criminal investigations (M = 286K) with adult offenders (N = 274K) in Bogotá (Colombia) between 2005 and 2018. The first component had 4,286 offenders (component 'A'), the second 227 ('B'), and the third component 211 ('C'). The evolution of these components was examined using temporal information in tandem with discrete choice models and simulations to understand the mechanisms that could explain how these components grew. The results show that they evolved differently during the period of interest. Popularity yielded negative statistically significant coefficients for 'A', suggesting that having more connections reduced the odds of connecting with incoming offenders in this network. Reciprocity and reinforcement yielded mixed results as negative statistically significant coefficients in ‘C’, and positive statistically significant coefficients in ‘A’ were observed. Moreover, triadic closure produced positive, statistically significant coefficients in all the networks. The results suggest that a combination of growth mechanisms might explain how co-offending networks grow, highlighting the importance of considering offenders’ network-related characteristics when studying accomplice selection. Besides adding evidence about triadic closure as a universal property of social networks, this result indicates that further analyses are needed to understand better how accomplices shape criminal careers.

6.2 Introduction

Crimes can be committed either by individuals or by groups of people acting together. While there are some contexts in which the involvement of multiple offenders is incidental - it plays no material role in the commission of the crime - there are others where it is a crucial ingredient: a crime could not, or would not, take place without it (Tremblay, 1993). Therefore, and as mentioned in Chapter 2, the study of co-offending has both theoretical and practical value. As well as providing insights into criminal behaviour, understanding how criminal collaborations arise may suggest ways to disrupt the conditions that facilitate crime-related activities. Within this, a particular topic of interest is accomplice selection - i.e., how offenders choose their criminal partners. While this has been discussed extensively from a qualitative perspective, there has been little attempt to examine it using a quantitative networked approach (for exceptions see, e.g., Cornish & Clarke, 2002b; McCarthy et al., 1998; Weerman, 2003, 2014)

Several theories have been proposed to explain accomplice selection and, in particular, to suggest which factors influence the choice of co-offender (see Weerman (2014); van Mastrigt (2017) for reviews and Chapter 2). Some of these focus on the role of personal characteristics - such as age, gender and criminal aptitude - or discuss the influence of the social environment more generally; the idea that offenders tend to commit crimes with others from their social circle, for example. Others, however, relate to previous offending behaviour: individuals may be more likely to form new collaborations if they have already co-offended with multiple individuals in the past, for example, while others may tend to repeatedly offend with the same accomplices (Charette & Papachristos, 2017). Hypotheses such as these relate to the influence of prior co-offending relationships on the formation of new ones, which are the focus of this study.

Networks provide a natural framework for studying these effects. Social network analysis has helped revive interest in co-offending in recent decades by providing tools and theories to study the interactions between individuals systematically (Bright & Whelan, 2020; Carrington, 2014; Papachristos, 2011). In co-offending networks, individuals are linked based on the crimes they have co-executed: the network is composed of *nodes*, representing individuals, and any pair of offenders who have co-offended are connected by an *edge*, representing the criminal event in which they participated. Since edges represent co-offending relationships, understanding the mechanisms which drive network formation is equivalent to understanding how these relationships arise.

This study seeks to gain insights into the principles that drive co-offending by analysing the growth of three network components representing co-offending relationships in Colombia's capital city, Bogotá, between 2005-2018.[1] In particular, the links formed due to each criminal event during the study period are examined. Each link formation represents the selection of an accomplice: conceptually, this selection might represent an explicit choice (e.g. recruitment), or it might reflect a more passive process (e.g. shared circumstance). In either case, identifying regularities in how these selections occur will offer insights into how co-offending relationships develop.

Understanding how co-offending networks evolve over time is crucial for identifying the mechanisms which drive their formation. Apart from a few contributions (e.g., Sarnecki, 2001; Charette & Papachristos, 2017; Iwanski & Frank, 2013; Brantingham et al., 2011), the studies that have adopted a network approach to study co-offending have analysed static networks. Static networks are snapshots that aggregate co-offending relationships into a single network, regardless of when the crimes were executed (Faust & Tita, 2019). The analysis of such networks can provide insights to understand the properties of co-offending networks better; however, they cannot reveal how these networks evolve through the decisions made by offenders when creating new relationships. As has been shown for networks in general, different underlying formation processes can lead to graphs with indistinguishable properties when analysed in the aggregate (Mitzenmacher, 2004).

This article starts to fill this gap by studying how co-offending networks evolve over time. Specifically, it applies a recently developed approach in network science that considers the formation of social networks as the result of choices made by nodes (offenders, in this case) when joining a network (Opsahl & Hogan, 2011; Overgoor, Ben-

[1] The terms growth and evolution are used interchangeably.

son, & Ugander, 2019; Feinberg et al., 2020). When a node joins a network - or, if it is already part of it, creates a new connection - it selects a 'target' from the pool of nodes that are already part of the network. Discrete choice modelling examines whether the features of the potential targets influence this selection by comparing the characteristics of chosen nodes to those that were not. Identifying these influences can shed light on offenders' decisions when selecting accomplices for new criminal ventures. This study focuses on network-related characteristics, such as the number of existing links or the presence of reciprocal connections. Since these features reflect prior offending connections, they can be used to make inferences about the role of existing relationships in guiding new ones.

At least four mechanisms can explain the growth of networks in terms of nodes' preferences for particular network-related properties. These have been examined in discrete choice studies of other social networks (Opsahl & Hogan, 2011; Overgoor et al., 2019). These mechanisms are popularity, reciprocity, reinforcement, and triadic closure - each of which can be interpreted in terms of offender behaviour. Popularity refers to the tendency of offenders to form links (i.e., co-offend) with those who already have many connections (i.e., recurrent or prolific co-offenders). Reciprocity refers to offenders selecting individuals who have previously selected them, while reinforcement describes the situation in which one individual re-selects another. Triadic closure describes the tendency to create links with the associates of prior associates ('co-offending with the accomplice of my accomplice').

The analysis relies on a discrete choice model with network features corresponding to these four growth mechanisms to study their relative roles in accomplice selection. This approach was used to analyse three components observed in a co-offending network in Bogotá

(Colombia) between 2005 and 2018, containing 4,286 (component 'A'), 227 (component 'B'), and 211 (component 'C') individuals. These components were derived from criminal investigation records and included all crime types defined by Colombia's criminal law; therefore, they reflect criminal collaboration in a general sense rather than in the context of any particular offence.

Theories of co-offending conceptualise accomplice selection as a fundamentally directional process in which individuals acting as recruiters instigate collaborations with others (Reiss, 1988); indeed, directionality is implicit in the four mechanisms outlined above. For this reason, the underlying model of the co-offending network is a directed graph, with orientation reflecting recruitment. This, however, presents an analytical challenge since the data does not contain information about which offenders acted as recruiters. It was addressed by adopting a procedure in which the analysis is repeated multiple times, with the directionality of edges randomised in each case: any findings robust to the choice of orientation can be assumed to apply generally. This approach was followed because a method that disregarded directionality would not reflect the nature of co-offending (as per the mechanisms identified above) and would be of limited theoretical value.

Theoretical and practical implications derive from this article. From a theoretical perspective, this study suggests that a combination of growth mechanisms might explain how co-offending networks grow, highlighting the importance of considering offenders' network-related characteristics when studying accomplice selection. It also highlights the importance of former accomplices, as the results suggest that they may act as sources of information for potential new accomplices. From a methodological perspective, this study demonstrates a recently-developed approach to studying how networks evolve over time which has not previously been applied in criminology. Researchers interested in studying co-offending or covert networks might employ this approach to study the formation of crime-related networks.

Practitioners can also benefit from this study as it shows how to exploit existing information to identify and track the evolution of co-offending networks. From a strategic perspective, understanding the mechanisms at play in the evolution of particular networks can offer practitioners insights which may inform the design of crime prevention strategies. Similarly, studying the evolution of co-offending networks can assist practitioners in assessing the effectiveness of their interventions. The proposed approach can help evaluate the interventions' effectiveness by analysing the behaviours a network displays after an intervention.

6.3 Background

Co-offending is a topic that has been discussed extensively within criminology, and several theories - often based on qualitative studies - have been proposed to explain the features and dynamics of group offending (Weerman, 2014). On the particular topic of accomplice selection, several perspectives have been advanced, discussing how offenders become aware of potential partners and how they evaluate their value as prospective co-offenders (van Mastrigt, 2017). These theories lay along a continuum: at one end are those which discuss collaborations that arise spontaneously, while others conceptualise accomplice selection as a rational process in which offenders seek to choose partners who will be of maximum benefit.

This section discusses some of these theoretical principles, which relate to the influence of prior collaborative behaviour on accomplice selection. In a network context - where links represent instances of co-offending - these theoretical principles correspond to models of link formation based on network-related features. In each case, the principle is discussed from a criminological perspective and its interpretation regarding network growth. In doing so, the conceptualisation of a co-offending network is as a *directed multigraph*; that is, a network which can have multiple links between any pair of nodes and where each link has an orientation. Multiple links represent distinct instances of co-offending, and the orientation reflects the initiation of the collaboration (i.e., recruitment).

6.3.1 Popularity

One suggestion that has been put forward in the literature is that individuals are more likely to be chosen as accomplices if they already have multiple co-offending connections (e.g., Sarnecki, 2001). Such individuals can be considered 'popular' from a co-offending perspective because they have frequently been selected as accomplices. The mechanism is analogous to the 'rich get richer' principle for social networks, whereby individuals forming new links preferentially attach to those who are already well-connected (Newman, 2018).

There are two reasons why popular co-offenders may be preferred as potential accomplices. First, their popularity may be attractive in itself, implying that the individual is an experienced co-offender, and their existing co-offending relationships may be seen as a form of endorsement. On the other hand, popularity may act as a marker of the individual's underlying utility as a criminal partner: it is not popularity *per se* that is attractive, but rather that individuals become popular because of their aptitude for crime. Certain characteristics or assets can affect the value that an individual can contribute to a potential criminal collaboration. These characteristics - referred to as 'criminal capital' - may include information, skills, contacts and personality traits (e.g., trustworthiness) deemed beneficial for the execution of a crime (Reiss, 1986; McCarthy et al., 1998; McCarthy & Hagan, 2001; Hochstetler, 2014). Those with these features will, in principle, be more attractive as potential accomplices and therefore selected more frequently. In this way, the popularity of an offender may simply be a proxy for their criminal capital.

When *popularity* plays a role in the growth of a network, it is likely that a small subset of individuals will form disproportionately high numbers of connections. This can, however, be manifested in two ways. In the first scenario, the connections are formed with distinct individuals, meaning that the popular nodes have many neighbours. In the second scenario, some of the connections relate to the same co-offenders (i.e. they are multi-edges), reflecting the fact that they have interacted on multiple occasions. In the first scenario, popular nodes have numerous neighbours, but their connections tend to be 'weak' as they represent single events. In the second one, popular nodes may not have as many neighbours as in the first scenario, but their connections will be 'stronger' or heavier. This scenario echoes McGloin et al. (2008)'s findings about how frequent offenders create stable co-offending relationships. If popularity were a prevalent mechanism in co-offending networks, a small subset of offenders would be expected to form many links, either with different associates (first scenario) or with the same ones repeatedly (second scenario). As explained in the following section, both scenarios were considered when analysing the growth of co-offending networks.

However, popularity might also be unattractive to potential accomplices. As offenders make more connections, their visibility increases and with it does their risk of getting arrested (Morselli, 2009). Accordingly, popularity may have a negative effect on accomplice selection in some circumstances, and its overall role in the growth of co-offending networks is not straightforward. Offenders with ample criminal capital will make more or stronger connections, but their attractiveness as potential accomplices may be short-lived since their popularity makes them prone to be removed by law enforcement agencies (LEAs).

6.3.2 Reciprocity and reinforcement

Two further mechanisms that may play a role in the growth of co-offending networks are *reciprocity* and *reinforcement*. The mechanisms are similar in that they both refer to the formation of multiple links between pairs of offenders but differ in their directionality.

Reciprocity refers to situations in which offenders select accomplices who have previously selected them - i.e., A selects B, having previously been selected by B themselves. In network terms, this corresponds to the tendency for pairs of nodes linked in one direction to be linked in the opposite direction. Such situations may arise when pairs of offenders repeatedly collaborate, each offender instigating on different occasions. Research has found that offenders do not have fixed roles throughout their criminal careers; rather, they alternate between the roles of 'recruiters' and 'followers' (Van Mastrigt & Farrington, 2011).

Conceptually, reciprocity refers to the likelihood of observing two individuals exchanging benefits or services over time - 'doing for others if they have done for them' (Plickert, Côté, & Wellman, 2007; Gouldner, 1960). This exchange is not mediated by an explicit negotiation or a power imbalance between participants. Instead, it is an exchange explained through social norms or self-interests of the parties involved (Molm, 1997). Reciprocity in co-offending has been analysed from the perspective of individual events but not to predict new co-offending relationships. For example, the *social exchange theory of co-offending* proposed by Weerman (2003) describes co-offending as a reciprocal interaction between co-offenders: co-offenders exchange material and immaterial goods to access rewards hard to obtain by solo offending. However, this mutual interaction primarily relates to collaborations themselves rather than accomplice selection.

Reinforcement, on the other hand, refers to instances where individuals repeatedly re-select the same accomplices (Grund & Morselli, 2017; McGloin et al., 2008), thereby strengthening existing connections between connected pairs (Gouldner, 1960). From a network perspective, these repeated interactions can be represented by multiple links - or 'heavier' links - connecting pairs of nodes. This tendency might be expected due to the cost or risk of forming new co-offending relationships. When committing an offence, it is easier and safer to renew a previous collaboration than to initiate a new one. Reinforcing existing relationships might also be expected when accomplice selection is viewed as a rational process (van Mastrigt, 2017). Accomplices liaise with those with the criminal capital that matches the needs for successfully executing the crime at hand. Hence, reinforcing existing relationships might reduce the costs of finding new associates with the skills needed to exploit new criminal opportunities. Moreover, trust builds among those who co-execute a crime (Charette &

Papachristos, 2017). Hence, initial interactions between unknown offenders can help them gain trust in their accomplices, allowing them to stick together.

Reinforcement overlaps to some degree with popularity because repeated re-selection can result in the selected accomplice having a high number of in-links. The mechanisms are distinct, however. The principle of popularity is that an individual X may favour an accomplice simply because of their number of prior connections; whether those connections are from X themselves is immaterial. With reinforcement, on the other hand, the preference is specifically for individuals whom they have chosen previously (with multiplicity irrelevant).

Reciprocity and reinforcement are similar in that they refer to the formation of multiple links between pairs of individuals but differ in *directionality*. As mentioned, the directionality in these relationships is closely related to the idea of recruitment (or instigation). Co-offending relationships are created when a person, acting as a recruiter, brings together other motivated offenders, who act as followers, to execute a crime (Reiss, 1986). Hence, these mechanisms are distinct, and both may play a role in explaining the empirical findings on how co-offending relationships are created and the behaviours offenders exhibit throughout their criminal careers. Both mechanisms were included for these reasons and used simulation analysis as a robustness check.

While both reciprocity and reinforcement represent plausible hypotheses, there is a large body of evidence concerning the instability of co-offending relationships. Numerous studies show that offenders are more likely to co-offend with new accomplices rather than stick with the same associates (e.g., Weerman, 2003, 2014; Warr, 2002, 1996; Carrington, 2002; McGloin & Thomas, 2016; McGloin & Piquero, 2010;

van Mastrigt, 2017). If this is the case, reciprocity and reinforcement may not play a role in how co-offending networks evolve; on the contrary, it might be expected that the presence of existing links has a negative effect on accomplice selection. However, research by Grund and Morselli (2017) has suggested that the instability of criminal partnerships has been overestimated in the literature due to a measurement issue. Using a method which adjusts for this, they find that the chance of a pair of offenders being arrested again is as high as 50%, contradicting prior studies and suggesting that reciprocity and reinforcement may play a role.

6.3.3 Triadic closure

Triadic closure refers to the tendency for new links to form between two unconnected individuals who share a common neighbour (Wasserman & Faust, 1994; Holland & Leinhardt, 1971). If A co-offends separately with B and C, triadic closure predicts that B and C will likely co-execute a crime.

Trust is often cited as a reason why social networks display this trait. Burt (2005) explained that when two people trust each other, there is a commitment to a relationship without knowing how the other person will behave. Two individuals sharing a connection to the same person will therefore have a basis to trust one another, increasing the chances of creating a new connection (Easley & Kleinberg, 2010). In these situations, trust emerges from the possibility of using informal sanctions to discipline the person breaking social norms (Coleman, 1988) - gossiping, for example, can be an informal sanction against those who break social norms. Similarly, trust plays a vital role in co-offending since offenders need to act together as planned without the need to supervise one another (Gambetta, 2011). Two willing offenders sharing an accomplice have a basis for trusting each other since the shared accomplice can arbitrate between them.

Accordingly, information about offenders' trustworthiness is essential for accomplice selection. McCarthy et al. (1998) contended that offenders rely on the information circulating in social networks to evaluate the trustworthiness of potential accomplices. Thrasher (1963) introduced a similar idea when referring to the underworld's 'grapevine system' in which information about offenders and their reputations circulate. In this sense, it is possible to hypothesise that triadic closure might play a prominent role in the evolution of co-offending networks. Two individuals with an accomplice in common are more likely to co-offend: the shared contact can vouch for each individual and act as a mediator if needed.

Feld (1981)'s *focus theory approach* provides an additional explanation for triadic closure in social networks. According to this theory, there are elements in the environment that act as *social foci* - settings in which individuals organise their social activities (e.g., family, workplaces, neighbourhoods). Feld suggested that two individuals sharing a connection to a third person might also share the same social foci, facilitating new relationships between unconnected pairs. Felson's (2003) notion of *offender convergence settings* resembles Feld's theory. In these settings, offenders contact potential accomplices to seize criminal opportunities and design criminal plans. Individuals sharing social foci (or offender convergence settings) are more likely to create new co-offending relationships than those not sharing these settings. This idea of people who share settings having more chances of creating new connections aligns with Granovetter (1973)'s explanation of triadic closure. If two individuals spend time with a third, they will likely encounter each other and potentially form a connection. The potential role of offender convergence settings is another reason triadic closure is expected to be prevalent in co-offending networks.

Relatively few studies have explicitly investigated the presence of triadic closure in co-offending networks; however, those that have done so (e.g., Grund & Densley, 2015; Nieto, Davies, & Borrion, 2022) have found evidence that it is indeed present. Nevertheless, the underlying mechanisms that give rise to it - for example, whether it is an effect in itself or a bi-product of convergence settings - remain unknown.

Figure 6.1 illustrates the four mechanisms described in this section. The review presented in this section suggests that popularity should be expected to play a relatively limited role in the growth of co-offending networks. Similarly, reinforcement and reciprocity might only partially explain the evolution of these networks, as most evidence suggests that co-offenders tend to find new accomplices as they continue their criminal careers. However, triadic closure seems likely to play a substantial role in the growth of co-offending networks since there is a clear overlap between the mechanisms which typically give rise to this trait in social networks and the principles driving co-offending selection.

Before going further, it is worth noting that these four mechanisms only consider nodes' network-related properties. These include the number of connections and their position in the network and exclude individual-level properties such as age, sex, or criminal history. The reason for focusing on these was partly practical - offender-level characteristics were not available in the data set (see Chapter 4) - but also theoretical: the primary interest is in how prior co-offending behaviours shape accomplice selection. Nevertheless, individual-level

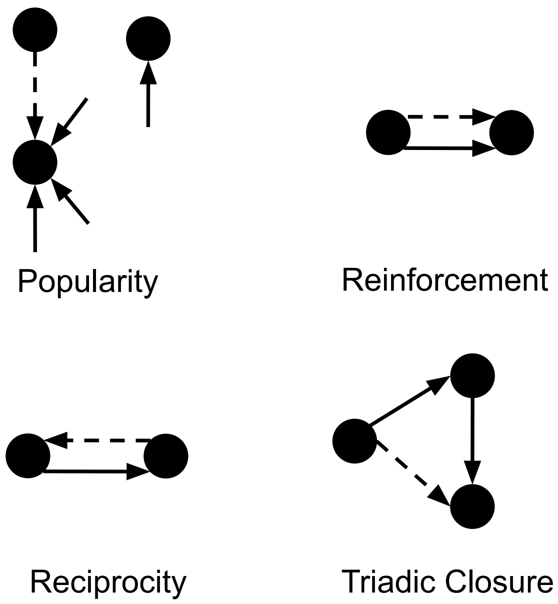


Figure 6.1: Based on the existing relationships (black solid lines), popularity, reinforcement, reciprocity, and triadic closure predict new connections between the nodes (dashed lines).

characteristics will also play a role (Robins, 2009), and their inclusion will be an essential topic for future work. It is also worth noting that edges' directionality is crucial to better understanding co-offending, as it allows better modelling of co-offending relationships as they are initiated by motivated offenders who recruit those willing to participate in the criminal venture. It also allows to differentiate between reciprocity and reinforcement. An explanation of how the edges' directionality was handled is included below.

6.3.4 Prior studies of network evolution

Although relatively little research has formally examined the evolution of co-offending networks from the perspective of accomplice selection, several studies offer important context. For example, Charette and Papachristos (2017), using a dynamic approach to analyse co-offending dyads, showed that the longevity of co-offending relationships - measured through the number of times pairs of offenders were co-arrested - tended to be short. However, they observed that a small proportion of relationships persisted. According to their findings, homophily (i.e., the tendency to create connections with similar others), experience (i.e., criminal capital), and transitivity (i.e., shared accomplices) might explain why some co-offenders stick together despite having previously been arrested together.

Another group of studies have analysed the evolution of covert criminal networks. Bright, Koskinen, and Malm found that triadic closure explained the structural changes experienced by a drug trafficking network comprised of 86 participants between 1991 and 1996 in Australia. Bright and Delaney (2013) also observed that drug trafficking networks were flexible and adaptive, as central offenders became peripheral when new individuals joined the network. Similarly, Morselli and Petit (2007), using information about a criminal investigation between 1994 and 1996 in Canada, observed that drug trafficking networks could become less centralised as LEAs try to disrupt them. While these are important insights, they are of limited relevance in the present context since the networks studied are primarily organisational rather than reflecting instances of co-offending. The networks model communication patterns between individuals participating in illegal activities as part of a wider enterprise, not the co-execution of individual crimes.

No studies have adopted a dynamic approach to analyse the evolution of co-offending networks, particularly regarding the mechanisms that guide the formation of links. Therefore, the question studied here - of how this evolution offers insight into the principles guiding accomplice selection - remains unanswered.

6.4 Method

6.4.1 Data and network construction

This study used the data described in Chapter 4. Bipartite networks were constructed using this data set, representing the associations between offenders (N = 274,689) and investigations (M = 286,591). Each link corresponds to a unique record in the data set, representing a connection between an offender and a criminal investigation. The one-mode projection of this network was used to derive a separate (undirected) network of associations between offenders (i.e. a co-offending network) (see Chapter 3 for an explanation of network projection). In this projected network, a link is placed between any pair of offenders connected to the same investigation; that is, two offenders have a co-offending relationship if they are both associated with the same CIRN. If two offenders shared more than one investigation, multiple edges were placed between them.

Of those individuals included in the network, 92,376 (34%) were co-offenders (i.e. had at least one link to another offender), with solo offenders (182,313) accounting for the remainder of the network (66%). The network had 32,348 components with two or more offenders. Of all investigations, 38% included a crime against private property, 27% a crime against people's physical integrity (e.g., assault), and 9% a crime against public safety (e.g., arms trafficking). On average, each offender was connected to 1.8 investigations, and each investigation included, on average, 2.5 offenders.

The largest component observed at the end of the study period included 4,286 individuals (component 'A'), followed by two others with 227 ('B'), and 211 ('C') offenders. The proportion of offenders in these components is small relative to the total number of offenders in the network. They represent less than 1% of the total number of offenders (as expected, given the low network density). Still, they constitute a substantial group when placed in the broader context. For example, the offenders in these components are equivalent to 44% of Bogotá's prison capacity or, since there is prison overcrowding in this city, 30% of the actual prison population as of December 2018 (National Penitentiary and Prison Institute - INPEC, 2021). Based on their significance in terms of the number of offenders, it was decided to study the growth of these components.

Table 6.1 presents some descriptive statistics of these components, and they are plotted in Figures 6.2-6.4. Each plot also includes a histogram showing the degree distribution and some descriptive statistics - the average degree centrality, diameter, density and clustering coefficient.

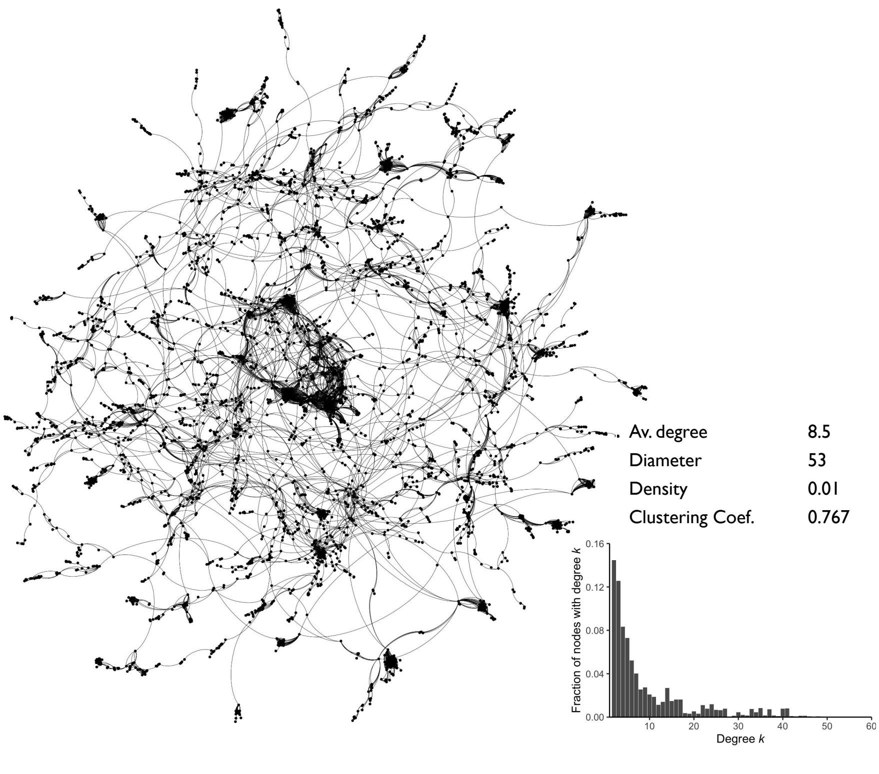


Figure 6.2: Component 'A'

Several similarities and differences can be seen in the structure of

Table 6.1: Descriptive network statistics: number of nodes, number of edges, number of investigations in the underlying bipartite structure, the mean number of offenders per investigation, the mean number of offenders per investigation, the mean number of investigations per offender, and the proportion of investigations linked to specific crime types.

	Complete Network	**Component A**	**Component B**	**Component C**
Nodes	274,689	4,286	227	211
Edges	136,270	18,165	1,226	5,615
No. Investigations	286,591	6,032	214	128
Avg. Number of Offenders per Investigation	2.5	1.89	2.3	3.1
Avg. Number of Investigations per Offender	1.8	2.6	2.1	1.8
Crime types (Proportion of investigations)	Property (38%) Physical integrity (27%) Public safety (9%) Others (26%)	Property (58%) Public safety (16%) Public Admin (6%) Others (20%)	Property (45%) Public safety (14%) Public admin (10%) Others (31%)	Property (46%) Public Admin (14%) Public Safety (14%) Others (26%)

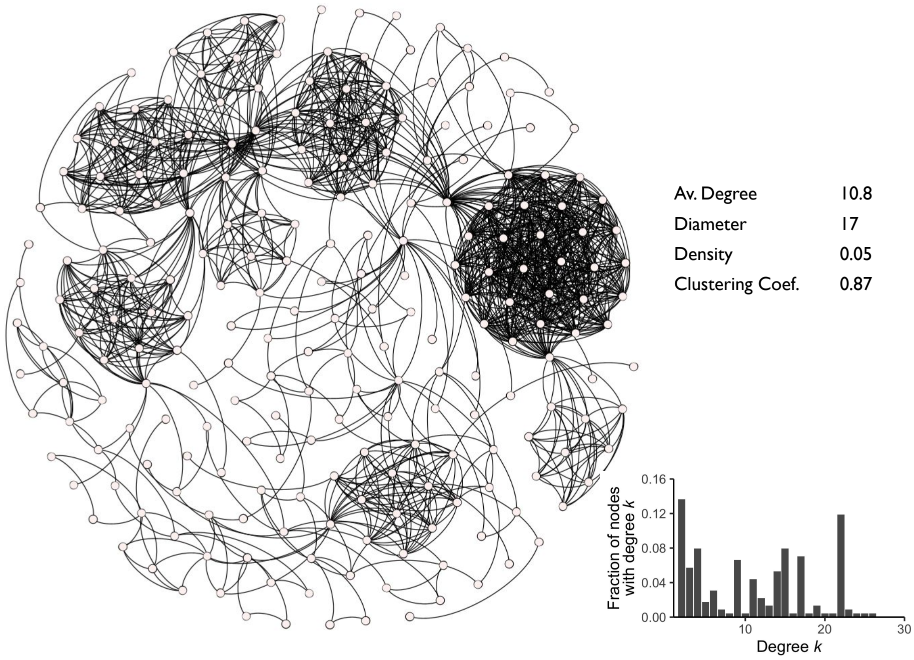


Figure 6.3: Component 'B'

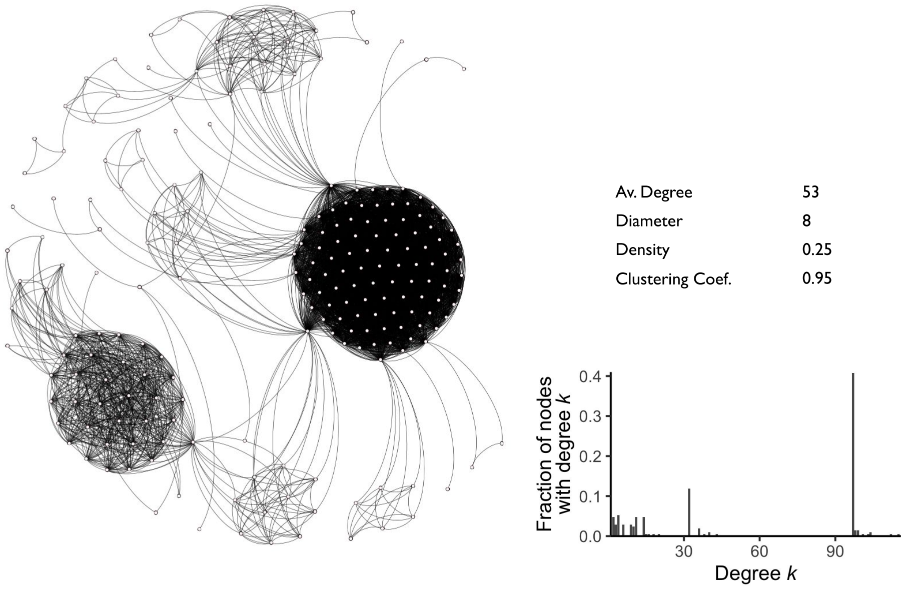


Figure 6.4: Component 'C'

the three components. Despite the difference in the number of nodes and investigations in the underlying bipartite structure, 'A' and 'B' had a relatively similar mean number of offenders per investigation (1.89 and 2.3, respectively), though the average degree in the latter was slightly higher (10.8) than the former (8.5). However, it is notable that 'B' contains some densely-connected clusters of nodes, which are likely to partly be a by-product of certain investigations with large numbers of participants. This is even more apparent in 'C', in which two particularly large clusters can be seen: again, this indicates the presence of large offending groups. This component had fewer investigations (128), a higher mean number of offenders per investigation (3.1), and a higher average degree (53). On the whole, however, 'A', 'B', and 'C' are relatively sparse networks and exhibit some transitivity in their connections (the clustering coefficients ranged between 0.77-0.95).

Regarding the proportion of investigations linked to specific crime types, almost half of the investigations in these components were related to crimes against private property. Offences against public safety (e.g., arms trafficking) and public administration (e.g., obstruction of justice) were also present in nearly one-quarter of the investigations in each component.[2] These components were not selected as representative of the complete network; they were chosen based on their size, as co-offending networks in their own right. Nevertheless, there was a resemblance between the entire network and the three components studied here. They all had a considerable proportion of criminal investigations related to crimes against private property. There was little variation in the average number of offenders per in-

[2]The classification followed by the Colombian Criminal Law to was used to group the crimes linked to each investigation. This Law groups crimes into broader categories based on the civil or human rights each crime type intends to protect.

vestigation and the average number of investigations per offender.

To get an initial understanding of the components' evolution, the data set was partitioned into *landmark windows* that encompass all data between a fixed start-point and sliding end-point (Cordeiro, Sarmento, Brazdil, & Gama, 2018; Gehrke, Korn, & Srivastava, 2001). Figure 6.5 shows a graphical representation of this approach, with the total number of offenders in the full network at each window. For the three components studied here, Tables 6.2a - 6.2c show the number of offenders, components, incoming nodes, and investigations observed in each sliding window. These components resulted from the coalescence of smaller clusters that merged and created a large connected component when new links formed 'bridges' between smaller fragments. The pace and proportion of incoming nodes varied between components (NB: the term 'incoming nodes' in these tables refers to new nodes joining the components. It excludes existing offenders creating new co-offending relationships).

6.4.2 Analytical framework

For the main part of the analysis, the formation of individual links in the co-offending networks was examined to gain insight into the mechanisms via which offenders select accomplices. This was achieved by employing a discrete choice approach first proposed by Opsahl and Hogan (2011) and similar to that used in subsequent work by Overgoor et al. (2019), Feinberg et al. (2020), and Overgoor, Pakapol Supaniratisai, and Ugander (2020). The model is an example of the more general discrete choice framework, which seeks to describe or predict the choices made by individuals from a discrete set of alternatives (McFadden, 1981). A random utility theory

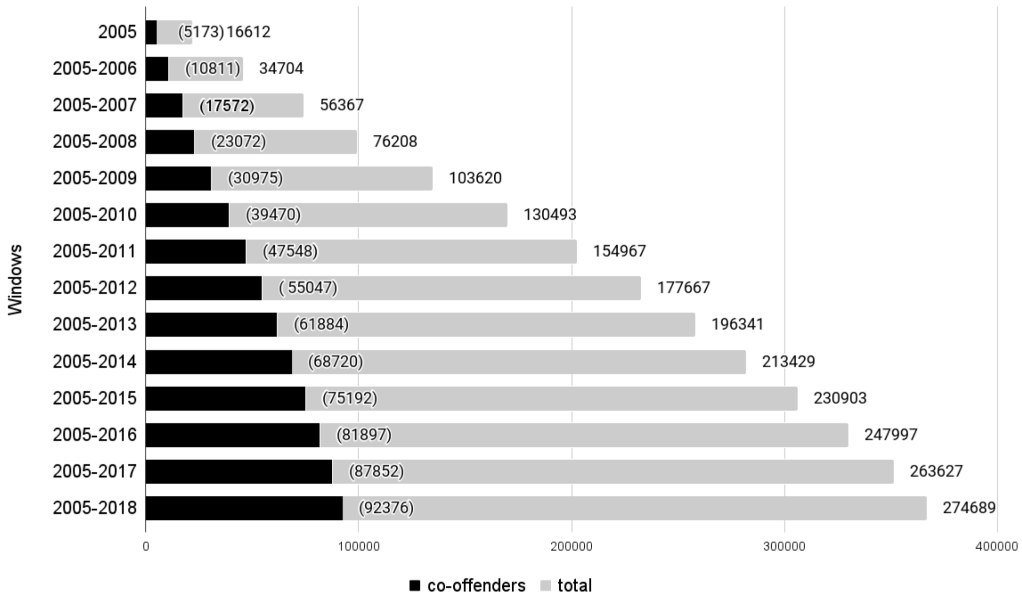


Figure 6.5: A landslide approach to partition the dataset. The y-axis displays the landslide windows, starting in 2005 (the landmark) at the top. The black bars represent the number of co-offenders with the number of co-offenders in brackets, and the grey bars represent the total number of offenders per window. Between 2005 and 2018, there were 274,689 offenders, of which 92,376 were related to at least one co-offence.

Window	Offenders	Components	Incoming nodes	Investigations
05	343	84	-	812
05-06	691	118	348	1577
05-07	1073	138	382	2263
05-08	1414	151	341	2738
05-09	1691	118	277	3173
05-10	2097	81	406	3799
05-11	2555	54	458	4333
05-12	2922	38	367	4702
05-13	3256	25	334	5105
05-14	3491	25	235	5364
05-15	3723	18	232	5619
05-16	3944	9	221	5846
05-17	4137	3	193	5959
05-18	4286	1	149	6032

(a)

Year	Offenders	Components	Incoming nodes	Investigations
05	13	6	-	8
05-06	19	9	6	13
05-07	30	15	11	24
05-08	36	19	6	31
05-09	43	21	7	42
05-10	53	25	10	55
05-11	72	26	9	73
05-12	87	27	15	89
05-13	103	32	6	112
05-14	112	29	9	129
05-15	128	29	16	149
05-16	143	24	15	172
05-17	189	19	46	195
05-18	227	1	38	214

(b)

Year	Offenders	Components	Incoming nodes	Investigations
05	3	3	-	3
05-06	15	6	12	7
05-07	22	8	7	15
05-08	26	11	4	19
05-09	32	12	6	27
05-10	59	12	27	36
05-11	68	16	9	54
05-12	86	16	18	68
05-13	201	2	115	77
05-14	203	2	2	88
05-15	207	2	4	99
05-16	207	2	-	107
05-17	211	1	4	118
05-18	211	1	-	128

(c)

Table 6.2: The number of offenders, components, incoming nodes, and investigations per window for each of the three networks considered here – (a) network 1, (b) network 2, and (c) network 3.

approach assumes rational actors make choices by considering the attributes of their options and choosing the one maximising their utility (McFadden, 1974). These models have been extensively used to explain decisions such as what colleges people attend, how they travel, or how they decide whether to enter the workforce (e.g., Train, 2009; Ben-Akiva, Litinas, & Tsunokawa, 1985; Simonson & Tversky, 1992).

In the discrete choice approach, the growth of the network is viewed as a sequence of link formations ordered in time. The key principle is to consider the formation of each link to be the outcome of a choice process, whereby one node has selected another to connect with from the set of all available nodes. By comparing the characteristics of the selected node to those of the nodes that were not, it is possible to infer which characteristics are favoured (or otherwise) when forming new links. In this context, where each association created represents a co-offence, any insights into the influence of particular network features can be interpreted in terms of the mechanisms driving accomplice selection. This approach captures two essential processes in co-offending: the first refers to the creation of new criminal relationships, and the second to the reinforcement or reciprocation of existing connections.

Formally, the model considers the formation of each edge in the network in sequence. For an edge (i, j) created at time t, it is assumed that node i could have chosen to form a tie with any node already present in the network at time t. This set of possible nodes is denoted A_t, and constitutes the *choice set* in discrete choice terminology. It is assumed that each node in this choice set has an associated utility, which is a function of its attributes and represents its *quality* as a potential connection. In the framework used here, this utility is assumed to take a linear form: if the attributes of each node k at time t are represented by a vector $Z_{k,t}$, then k's utility as a potential connection is a linear function of $Z_{k,t}$.

Under some assumptions about the random components of the utility (McFadden, 1974), it can be shown that the probability that j is chosen by i is given by:

$$P\left\{J_t = j | Z_t\right\} = \frac{\exp\left(\beta' Z_{j,t}\right)}{\sum_{k \in A_t} \exp\left(\beta' Z_{k,t}\right)} \tag{6.1}$$

where β' is a vector of coefficients. These can then be estimated via maximum likelihood (Hosmer Jr, Lemeshow, & Sturdivant, 2013).

6.4.3 Node attributes

The attributes incorporated in the model represent nodes' features; these can be either endogenous characteristics (e.g. age, sex) or network-related properties (e.g., the number of existing connections). The analysis focuses only on the latter, corresponding to the mechanisms that this study sought to test. The integration of endogenous features in this analysis represents an avenue for future research when such data becomes available.

Two variables were used to reflect nodes' popularity. A node's *in-weight* corresponds to the number of connections to it - i.e. the number of times that the offender has previously been chosen as an accomplice (including multiple times by the same individual). On the other hand, the *in-degree* of a node measures only the number of other nodes connected to it, even if some are connected by multiple links (i.e. multiple crimes). Reinforcement was coded as a binary variable: 1 if there was an existing link from i to j and 0 otherwise. Similarly, reciprocity was operationalised as a binary variable: it took the value

1 if there was an existing link from j to i and 0 otherwise. Triadic closure was measured as the number of accomplices shared by a pair of co-offenders. Note that these variables can evolve: if i forms multiple edges with j, for example, j's reinforcement value will be 0 the first time and 1 after that. For each choice, the values used for $Z_{k,t}$ were as they were at the point t when the corresponding choice was made.

Applying this discrete choice framework to the data requires meeting the assumptions of the underlying model. Discrete choice models assume that individuals act rationally when making a choice - i.e., they will select the option that maximises their utility from the available options. Based on the theoretical arguments reviewed in the previous section, this is justifiable in the context of accomplice selection. A common feature in accomplice selection theories is that offenders seek to maximise benefits and reduce costs when selecting accomplices (e.g., Cornish & Clarke, 2002b; Tremblay, 1993; Weerman, 2003). In doing so, they evaluate potential partners based on their perceived trustworthiness (to minimise the risk of betrayal) and the likelihood of this individual maximising the expected benefits from the criminal venture. This evaluation implies judging the 'criminal capital' of their potential accomplices: the skills, information, and contacts deemed beneficial for successfully executing a crime (McCarthy & Hagan, 2001; McCarthy et al., 1998). Since there is a strong foundation for the notion that accomplice selection is a rational process, discrete choice models are suitable for studying the growth of co-offending networks.

6.4.4 Analytical challenges

This study encountered three technical challenges. The first of these was computational. Each time a node makes a new connection, every other node currently in the component can be selected, creating a large and imbalanced choice set (i.e., dominated by non-selected nodes). This makes the estimation of models computationally expensive and can lead to biased estimates (Opsahl & Hogan, 2011). This can be addressed via negative sampling: rather than including all non-chosen alternatives in the choice set, only a smaller, randomly-selected sample - referred to by Opsahl and Hogan (2011) as 'control cases' - is included (Train, 2009). As long as this sample is chosen randomly, parameter estimates can be shown to be unbiased and consistent with those derived from the complete set. There is no general rule for the appropriate number of control cases; instead, it can be established via sensitivity analysis, which is presented in Appendix B. In this analysis, 30 control cases were used for 'A' and 10 for 'B' and 'C'.

The second challenge was related to the nature of the data. The discrete choice framework outlined above assumes - in line with accomplice selection theory - that the links in the network are directional; that is, an edge (i, j) refers specifically to i choosing j, rather than vice versa. In the co-offending network, however, links were undirected; it was known that a pair of offenders participated in an offence but not who instigated the link. To address this, the estimation of the model described in Equation 6.1 was completed 1K times, randomly assigning the direction of each link at each iteration. The logic of this approach was that, if findings were consistent across the iterations, then the underlying principles were not sensitive to the edges' directionality.

A third challenge related to investigations comprised of three or more offenders (see Table 6.1 for the mean number of offenders per investigation). Such investigations result in the simultaneous formation of multiple links; however, while in reality, they are formed simultaneously, the order in which they are listed in the data set affects the statistical analysis. For each choice scenario, the attributes of candidate nodes were calculated based on the current state of the network and before the connection between i and j was created. These attributes might change as more links are added since j can be selected more times or form connections with i's neighbours. To mitigate this, the ordering of links associated with each investigation was shuffled at each iteration of the analysis. Figure 6.6 illustrates this randomisation process. Again, the rationale was to remove any dependency of the findings on an arbitrary ordering of links. Overall, these randomisation procedures - directionality and ordering of links - meant that the model in Equation 6.1 ran for 1K realisations of each of the three components of interest. Given the computational demands, UCL's Cluster Computing Services were used to perform the analysis.

6.4.5 Alternative approaches

Using discrete choice models to study how social networks grow differs from other approaches that seek to identify the mechanisms driving networks' evolution. In some methods, the structural properties of the network at a single point of observation are used to deduce the process by which it reached its current state (Overgoor et al., 2019); for example, the degree distribution is commonly used to in-

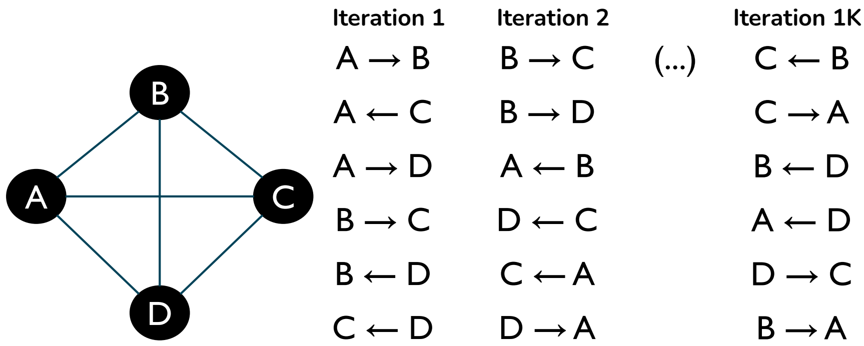


Figure 6.6: Starting with an undirected component (left), the order of the nodes in the edge list and the directionality of the edges between pairs of nodes were randomly assigned in each of the 1K iterations. The model described in Equation 6.1 was estimated in each iteration using the resulting random version of the edge list for the three components considered here.

fer whether a network has grown via preferential attachment. This approach has shortcomings, however, since different formation processes can lead to networks that are structurally indistinguishable (Mitzenmacher, 2004). This can be avoided when the ordering of edge formations is known. Here the timestamps attached to each criminal investigation were used to formulate each instance of accomplice selection as a choice.

The proposed approach was favoured over the stochastic actor-oriented models (SAOM) (Snijders, Van de Bunt, & Steglich, 2010). SAOM use panel data (i.e. snapshots of a relatively stable group of nodes) to model network dynamics using computer simulations. Since there was a considerable variation in the number of offenders observed in each temporal window (see Tables 6.2a - 6.2c), the panel data approach prescribed by SAOM was deemed unsuitable.

The proposed analytical framework also differs from Dynamic Network Actor Models for Relational Events (DyNAM) (Stadtfeld & Block, 2017). The statistical models in DyNam investigate coordination ties found in diverse social settings (e.g., scientific collaboration, international trade, and friendship). The idea of a mutual agreement between i and j to form a relationship is at DyNam's core; hence, the decision is two-sided, and the directionality of who chooses whom is irrelevant. However, this principle contradicts how co-offending relationships are formed, since, as outlined above, *instigation* is essential to understanding co-offending and gaining insights into crime prevention (Reiss, 1988). Accordingly, the directionality in the relationships between offenders is vital when studying co-offending, limiting the applicability of DyNam.

6.5 Results and Discussion

Popularity, reciprocity, reinforcement, and triadic closure were jointly tested to understand the evolution of three components of the co-offending network. To analyse their growth, models with two different specifications - one with in-degree as a proxy of popularity and the other with in-strength - were run. In each case, the estimation of the model was iterated 1K times, in line with the randomisation procedure outlined above.

The results across all models are summarised in Table 6.3, with coefficients shown for each component studied and each measure of popularity (see Appendix B for a graphical representation of the results). This table also includes the minimum and maximum C-statistic observed for each model (also known as the 'concordance' statistic or C-index), which is a measure of goodness of fit. According to the classification proposed by Hosmer Jr et al. (2013), the models used to describe the largest network can be considered as 'strong' models as their C-statistic is above 0.8. The models used for the other two networks are 'good' since their C-statistic is above the 0.7 mark - especially for 'C'. Accordingly, these models represent a good fit for the observed data.

Since the results are similar for both measures of popularity (in-degree and in-strength), the values for in-degree are used to illustrate the findings in the remainder of this section. The results reveal that the components evolved in different ways. Reciprocity, reinforcement, and triadic closure yielded positive, statistically significant coefficients for 'A', while in-degree generated negative ones. Accordingly, the odds of an offender connecting with a former recruiter (reciprocity) were 44 times higher than connecting to an offender who had not previously selected them ($\tilde{x}$ = 3.78; exp(3.78)=43.8). Similarly, the odds of observing an offender co-offending with a former associate were 13 times higher ($\tilde{x} = 2.6$) than co-offending with an offender with no previous connections (reinforcement). Likewise, the odds of co-offending with someone with whom incoming offenders had a mutual associate were four times higher for each additional accomplice they shared (triadic closure, $\tilde{x} = 1.46$).

Table 6.3: The median coefficient observed in the 1000 simulations and the minimum and maximum values of the C-statistic. *** denote those that yielded statistically significant (p-value <= 0.01) coefficients in all runs; ** in 9.4%, and * in 0.5% of the runs.

	Indegree	Reciprocity	Reinforcement	Triadic Closure	C-Statistic
4268	-0.018***	3.78***	2.6***	1.46***	0.915-0.919
227	-0.01*	-0.10	0.1	1.33***	0.665-0.741
211	0	-3.04***	-2.81***	0.39***	0.735-0.763
	Instrength	Reciprocity	Reinforcement	Triadic Closure	C-Statistic
4268	-0.016**	3.79**	2.61**	1.47**	0.92-0.925
227	-0.02**	-0.11	0.11	1.33***	0.673-0.745
211	0	-3.03***	-2.79***	0.38***	0.727-0.764

Component 'B' displayed a different behaviour. Triadic closure was the only mechanism that yielded statistically significant coefficients. In this case, the odds of an offender committing a new crime with someone with whom they have a mutual associate were four times higher for each additional accomplice they shared ($\tilde{x}$ = 1.33). 'C' was the only component that yielded negative statistically significant coefficients for reciprocity and reinforcement. Former recruiters were 21 times less likely to be selected by a former associate ($\tilde{x}$ = -3.03; exp(-3.03) = 0.048; 1/0.048 = 20.83). Likewise, incoming offenders were 16 times less likely to co-offend with someone they had previously selected ($\tilde{x}$ = -2.79; exp(-2.79) = 0.061; 1/0.061 = 16.4).

These results challenge the importance attributed to *popular* offenders in explaining how co-offending networks evolve (Sarnecki, 2001; Englefield & Ariel, 2017; Malm & Bichler, 2011; Bichler & Malm, 2018). Based on prior findings, positive, statistically significant coefficients for both proxies of popularity were expected. Instead, popularity only yielded negative statistically significant results for the largest component, suggesting that having multiple connections reduced the odds of an individual being selected for a subsequent collaboration. The increased visibility experienced by *popular* offenders could explain this outcome. As mentioned, those who have been subject to multiple criminal investigations are naturally more visible to LEA and have a track record of being 'caught'. Potential recruiters may therefore view them as a risky prospect from the perspective of co-offending.

In turn, these results point to the limited predictive power of popularity in forecasting how co-offending networks might evolve. It is worth noting that this limited predictive power could not be identified by only considering the degree distribution of a network snapshot (see, for example, Figure 6.2). This distribution shows that a large number of offenders had few links but that a small proportion had a large number of accomplices. On its own, this might suggest that some form of preferential attachment played a role in the network's evolution. However, by continuously observing its growth using the analytical strategy adopted here, it was showed that, despite the skewed distribution, popular offenders had only a marginal role in explaining the evolution of the components considered here. Note that the data included 'failed' (i.e., detected) co-offending relationships. Popular offenders who have not been arrested or prosecuted could still have prominent roles in expanding these components or linking unconnected components in the observed network. This is an inherent limitation of studies relying on official records to study crime, and it is further discussed in the final section of this Chapter.

Based on the results reported elsewhere about co-offending relationships being unstable (Weerman, 2003, 2014; Warr, 2002, 1996; Carrington, 2002; McGloin & Thomas, 2016; McGloin & Piquero, 2010; van Mastrigt, 2017), similar results to the ones seen for 'C' were expected in all cases. However, previous interactions increased the odds of observing former associates executing new crimes in 'A'. Moreover, neither reciprocity nor reinforcement yielded statistically significant coefficients for' B'. These outcomes suggest that in some networks, offenders are likely to re-offend with known associates. From a rational perspective, re-offending with the same accomplice might reduce costs linked to the search for new accomplices. Likewise, previous interactions might create and increase trust between pairs of offenders. While these explanations cannot be tested here, future research could combine the analysis conducted here and the approach proposed by Charette and Papachristos (2017) to understand the factors that might explain why some co-offenders decide to stick together.

The mixed results for reciprocity indicate that this mechanism might operate in contrasting ways. On the one hand, it can bring together offenders, giving rise to interactions of the sort 'offender A selects offender B', followed by 'offender B selects offender A', as seen in component 'A'. This sequence of events aligns with the earlier comments about how offenders alternate between the roles of 'recruiter' and 'follower'. Alternatively, recruitment can act as a 'repellent' between known associates, as seen in 'C'. Again, this effect could be explained by the transient nature of individuals' roles in co-offending relationships. Once an individual is instigated into a crime, they can become embedded into a criminogenic network of potential accomplices. As part of this network, this person can change roles based on the criminal expertise they acquire. Criminal expertise can help reduce the inherent risks of co-offending as people might feel less uncertain when committing a crime with a seasoned offender (Marie McGloin & Nguyen, 2012).

In interpreting the results concerning reciprocity and reinforcement, however, it is important to mention some caveats. The first is that the analysis is based on information about 'failed' co-offending relationships; *i.e., those detected by LEA*. This might explain why recruitment acts as a repellent: followers could be more inclined to seek new accomplices and avoid former recruiters based on their unsuccessful ventures. Accordingly, followers might look for seasoned criminals that could reduce detection risks. The second caveat is analytical. Because the analytical procedure involved the randomisation of link directions, it is not possible to discriminate between reinforcement and reciprocity; recruiters were unknown in each case. However, the fact that findings persist across the 1,000 iterations suggests that the findings are not spurious. In addition, the results for both mechanisms mirror each other - the direction and significance of the effects are the same in all models - indicating that they operate (or not) in tandem.

Triadic closure plays a consistent role in explaining the emergence of co-offending relationships across all components. This result suggests that former accomplices might be essential in procuring potential associates. It also supports the importance of the information circulating in the 'grapevine system' (McCarthy et al., 1998; Thrasher, 1963) that facilitates finding partners and, ultimately, the execution of a crime (Tremblay, 1993).

6.6 Conclusion

The analytical strategy employed here shows how to consider multiple mechanisms when the data at hand allows researchers to observe how new connections are created in an ordered sequence. According to the results, the evolution of co-offending networks, as in other social networks, could be partly explained by the interaction of multiple mechanisms (Hedström & Swedberg, 1998). Specifically, popularity was found to either be unattractive or play no role at all, while there were mixed outcomes for reciprocity and reinforcement. On the other hand, triadic closure showed consistently positive results. Moreover, the results also indicate that the models used provided either a 'strong' (for the largest component considered here) or 'good' (for the other two) fit to the data.

Using a discrete choice approach to study the evolution of networks offers an alternative to previous techniques that relied on aggregated information (e.g., degree distribution) to examine how co-offending networks grow. A static network analysis might mask essential drivers of the growth of co-offending networks. Despite the limited number of networks considered here, this paper contributes to the scarce literature that has included a temporal dimension in the analysis of criminal networks (Bright & Delaney, 2013; Charette & Papachristos, 2017; Bright et al., 2019). This work sets a basis for future analyses of similar covert networks to grasp their evolution mechanics.

This analysis included four network-growth mechanisms, but, as explained by Overgoor et al. (2019), the integration of discrete choice models and network evolution is flexible enough to consider more and more complex mechanisms and integrate information such as node-level characteristics (e.g., age, sex, or prior history in the criminal system). Future research could incorporate precise information about who selected whom and use node-level information to verify findings about recruiters' characteristics. For example, Van Mastrigt and Farrington (2011) reported that recruiters tend to be older than followers in juvenile co-offending relationships; however, there are no reports about recruiters' traits in adult co-offending.

Future research could also include geographical information (e.g., place of residence and where offenders committed the crimes) to gain more insights into how adult co-offenders select their accomplices. Including such information would be useful, especially when considering the mechanisms, such as triadic closure, with a geographical component as an underlying explanation (i.e., social foci/offenders' convergence settings). Incorporating more information when analysing the evolution of co-offending networks will help better understand crime's aetiology and how to prevent the emergence of new co-offending relationships.

Besides including node-level and geographical information, future research could examine co-offending networks through a *multilayer* approach. Multilayer networks consist of a fixed set of nodes connected by several different types of connection, represented by multiple layers (Newman, 2018), and have been studied across a wide range of contexts (Kivelä et al., 2014). However, studying criminal networks through multilayer networks is rare and has been limited to organised crime research (e.g. Ficara, Fiumara, Meo, & Catanese, 2021; Ficara, Fiumara, Catanese, De Meo, & Liu, 2022). In the present context, co-offending networks could be studied using a multilevel approach using different layers to represent specific crime types or time frames. Disaggregation by crime type has particular potential in this regard: this could be used to examine whether co-offending patterns differ across crime types, or whether individuals tend to repeatedly collaborate on particular types of crime (i.e. specialise). Comparing and contrasting the layers in these networks can shed light on co-offenders' behaviours, which is an opportunity to refine this work.

This analysis is subject to some limitations, primarily relating to data availability. Although the underlying model framed accomplice selection as a directional process, with relationships initiated by offenders acting as recruiters, the data used here did not capture this trait. Future research could incorporate precise information about directionality once it becomes available. Furthermore, individual-level attributes of offenders (e.g. age, sex, ethnicity) were not included in the data set shared by the AGO, meaning that the analysis focused exclusively on the role of prior co-offending relationships. While this addresses several theoretical mechanisms, it is clear that individual-level features will also play a role in determining 'criminal capital' and therefore influencing accomplice selection (Robins, 2009). Information on the incarceration or death of individuals was also missing from the data set. Both of these would have implications for the analysis since they would mean that such individuals are not available for selection by others (i.e., they are excluded from the choice set). In particular, it constitutes a caveat to the results concerning popularity since popular offenders (i.e., prolific) are more likely to be unavailable. However, this issue is less likely to be problematic for reinforcement and reciprocity since any incarceration due to a prior offence is likely to affect both partners simultaneously. More generally, it is important to note that the fact that an offender was subject to an investigation did not preclude them from making new connections: while under investigation or on trial, they may still commit crimes.

More generally, since the study is based on LEA's data, it suffers from the inherent limitations of official records used to study criminal networks (Campana & Varese, 2020) (see also Chapter 4). Most notably, attrition at various stages of the criminal justice system means that officially-recorded crime represents only a subset of all crime occurring, with the remainder representing a 'dark' figure. Victims may fail to report crimes they suffer, or LEAs may overlook crimes once victims come forward (Carrington, 2014; Campana & Varese, 2020). Furthermore, prosecutors might fail to identify any or all those involved in a criminal event, resulting in a closed investigation or missing connections between offenders (i.e., co-offending networks with missing links). This issue is common to all studies of crime which rely on official records; however, such records are the only viable source of data concerning co-offending at a large scale and are used as the basis for almost all research on the topic.

Some decisions were taken to minimise the impact of these data issues. Information about all ongoing and closed investigations over a relatively long period (14 years) was included. Moreover, the data resemble two sources of information commonly used to study co-offending - arrest records and court files. These sources are typically used separately and rarely combined. Ongoing investigations represented arrest records because every person arrested in Colombia needs to be linked to a criminal investigation. It also resembled court records because it included information about closed cases with a guilty verdict and those where the offenders pleaded guilty. Furthermore, information on all possible crimes was included, capturing different organisational practices within the AGO, not those of a particular task force.

These limitations should be considered when interpreting the findings. It is possible, for example, that under-recording means that the popularity of some offenders was underestimated, which might mean that the role they played in network formation is not captured. Furthermore, some missing links may connect components in the network, meaning its fragmentation is not as great as it may appear. In simple terms, the findings may provide an incomplete picture of co-offending relationships. However, it should also be noted that, from a practical point of view, findings relating to officially recorded offending are still of value, even if not wholly representative of the overall situation. LEAs can only disrupt offending of which they are aware - if an offence never comes to their attention, it cannot be a target for prevention - and so, to some extent, recorded crime is a population of interest.

Chapter 7

Assessing Criminal Specialisation in Co-offending Groups

7.1 Overview

Researchers have studied criminal specialisation at the offenders' level to understand criminal careers. It is less known whether co-offending groups show signs of becoming specialists despite criminal careers being comprised of events where offenders co-offend with others. This Chapter presents a method through which 1,796 co-offending groups were identified in a network containing information about adult offenders (n = 76,697) connected to criminal events (m = 35,604). One in five co-offending groups remained unchanged in their composition and re-offended. Of those re-offending, 54% became specialists in crimes such as those affecting private property. The other 46% that re-offended were generalists. Simulation analyses showed that the proportion of highly specialised groups was not observed by chance. The results suggest that criminal specialisation is a characteristic also displayed by co-offending groups. Criminologists and practitioners might find the method employed here to identify co-offending groups and assess their level of specialisation helpful.

7.2 Introduction

Criminologists have devoted significant attention to studying *criminal careers*; that is, the sequence of offences committed by a person during a specific period (Blumstein, Cohen, & Farrington, 1988). Within this field, researchers have attempted to determine whether offenders tend to commit a wide range of crimes or, instead, specialise in particular crimes (e.g., Blumstein, Cohen, Das, & Moitra, 1988; Britt, 1996; Farrington, Snyder, & Finnegan, 1988; Roach & Pease, 2016). In general, adult offenders have been found to specialise in specific crimes during short periods during their criminal careers (i.e., *spurts of specialisation*) (e.g., Deane, Armstrong, & Felson, 2005; Sullivan et al., 2006; McGloin, Sullivan, Piquero, & Pratt, 2007; Steffensmeier & Ulmer, 2017; Shover, 2018). However, this research has focused almost exclusively on solo offending and given little consideration to the behaviour of offending groups. Criminal careers include solo offences and those committed with others (co-offending), and criminal collaboration gives rise to several distinctive phenomena (Reiss, 1986; Reiss & Farrington, 1991; Reiss, 1988; Tremblay, 1993). The limited research on the criminal specialisation of co-offending groups suggests that juvenile groups specialise in some crimes (e.g. Warr, 1996; McGloin & Piquero, 2010). Similarly, Grund and Morselli (2017) showed that pairs of offenders (or *dyads*) also show evidence of specialisation. Apart from these contributions, however, research on specialisation in co-offending is limited. Evidence does not support (or reject) the claim that co-offending groups are specialised in general.

Understanding criminal specialisation has theoretical and policy implications. Some crime theories (outlined below) make assumptions about offenders' tendencies to become specialists or generalists; developing new evidence about offender specialisation might, therefore, be helpful to refine or falsify them (Sullivan et al., 2006). As an example, Mazerolle et al. (2000) suggest that differential opportunity theory (Cloward, 1960) predicts the emergence of deviant subcultures (norms and rules created by deviant groups) in neighbourhoods, which in turn leads to local concentrations of particular types of offending. Deviant subcultures can be conducive to certain forms of crime, such as violent crimes (i.e., *conflict subcultures* resulting in 'turf wars' between gangs) or drug trafficking (i.e., *criminal subcultures* in which organised crime groups recruit youths to participate in illegal activities as couriers, for example). Consequently, criminal specialisation patterns would be shared between people living in the same area due to the existence of these deviant subcultures. Other theories suggest that offenders can engage in numerous types of criminal activity and, rather than favouring any particular type, are simply pre-disposed towards offending in general. For instance, Gottfredson and Hirschi (1990)'s theory posits that illegal activities are committed by individuals who lack self-control. Due to the lack of self-control, individuals would favour opportunities that are easy to seize and deliver immediate gratification (i.e., low-hanging fruits), making them prone to becoming generalists (Mazerolle et al., 2000). Theories of crime such as these make assumptions about the behaviours displayed by individual offenders; however, they tend to exclude the behaviours offenders display when co-offending. Accordingly, understanding the tendency to which co-offenders specialise in specific crimes can move the field of studies of criminal careers forward. Specifically, it is necessary to understand the relationship between the spurts of specialisation and co-offending (if any).

Policymakers may find it helpful to understand the criminal specialisations of co-offending groups to design interventions aimed at preventing criminal activity. These interventions, especially those conducted when groups first show signs of specialising, might help disrupt individuals' and groups' behaviours. This disruption would prevent groups from developing the necessary criminal capital (e.g., skills, information, contacts - see Chapter 2) to continue committing the same crime type or force them to seek new opportunities (e.g., trying out a different crime type). In either scenario, the 'cost' of offending would be increased, and some (temporary) reduction in crime would be expected. Such an approach is aligned with the rational choice perspective, which suggests that if the relative rewards of crime are offset by the effort and/or risk involved in adapting behaviours (*e.g.* switching to other crime types), then the crime may be prevented (Cornish & Clarke, 1987). Indeed, evidence shows that displacement across offences is not typical (Guerette & Bowers, 2009). Accordingly, understanding the criminal specialisation of co-offenders - coupled with tools that help understand how crimes are executed like crime scripts (Cornish & Clarke, 2002a) - can assist law enforcement agencies in deciding how to allocate the limited resources they have (Morselli, 2009).

Criminal specialisation among adult co-offenders is explored using a dataset containing information about criminal investigations in Bogota (Colombia) between 2010 and 2018. Co-offending groups were identified in a network representing the relationships between offenders ($n = 76,697$) and criminal events ($m = 35,604$) and assessed their level of criminal specialisation (or diversity). The versatility of each co-offending group was measured using the *diversity index* proposed by Agresti and Agresti (1978). This index represents the probability that any two random offences committed by a co-offending group belong to different types of crime and has been applied before to measure the criminal specialisation of individuals (Mazerolle et al., 2000; Grund & Morselli, 2017; McGloin et al., 2007; Piquero, Oster, Mazerolle, Brame, & Dean, 1999).

The findings indicate that one in five co-offending groups remained unchanged in their composition and re-offend. Of those re-offending, half would show signs of becoming specialists, while the other group tended to become generalists. Moreover, highly specialised groups differ from non-specialised groups regarding the time they remained active during the study period and the distribution of crime types in which they participated.

This study aims to contribute to the literature on criminal careers and co-offending by examining the degree of specialisation of co-offending groups. As explained, this question has received less attention than specialisation at the individual offender level. It also aligns with the premises of networked criminology (Bichler, 2019; Papachristos, 2011), as it further develops a shared understanding of network science techniques to study crime by showing how to identify co-offending groups in bipartite networks (i.e., networks representing the relationships between offenders and criminal events).

7.3 Co-offending groups and criminal specialisation

As discussed in Chapter 2, most evidence of co-offending groups comes from Canada, Sweden, the UK, and the USA. Research on adult co-offending in general, and co-offending groups in particular, is limited outside these countries. Studies in the field have primarily focused on the composition and dynamics of the groups themselves rather than their activities. While it has been shown that juvenile co-offending groups tend to be small and short-lived, for example, the extent to which they become specialists or generalists is unclear. Moreover, comparing results from the field is challenging because of the lack of a concise and consistent definition of what should be considered a *co-offending group*. The transient nature of relationships between co-offenders means that collaboration can be defined in multiple ways, and some studies focus only on a limited range of crime types.

Co-offending groups are typically small, consisting of only a few offenders, although results differ across age groups and settings. It is common, for example, for juvenile offenders to commit crimes with only one accomplice, thus limiting the size of co-offending groups (Reiss, 1988; Reiss & Farrington, 1991). More generally, Carrington (2014) summarised findings for all ages published before 2011 and found that those in Canada and England exhibited a similar pattern, while those in the USA behaved differently. Nearly 70% of the observed groups in Canada and England had two offenders, while this was the case for only 39% of those observed in the USA. Conversely, while the proportion of groups with four or more co-offenders was relatively small in Canada and England (7%), 31% of those observed in the USA had four or more members. While this might indicate that co-offending groups are more prominent in the USA, the time frame of the studies (Canada, 1992-1999; England, 2002-2005; and the USA, 2008) and data sources (criminal incidents recorded by the police in Canada and England, and victimisation reports in the USA) could explain the differences. It has also been found that the size of a group is related to the age of the offenders. Once juvenile offenders reach their mid-20s, group sizes decline, and large co-offending groups become rare. If they continue their criminal careers after this age, offenders tend to switch to solo offending (Reiss, 1988; Warr, 2002; Carrington, 2002).

It has consistently been shown that co-offending groups tend to be short-lived (or unstable), with offenders regularly changing associates (Carrington, 2002; McGloin & Piquero, 2010; McGloin & Thomas, 2016; Reiss & Farrington, 1991; Weerman, 2003, 2014; Warr, 2002, 1996; van Mastrigt, 2017). Continued offending with the same accomplices appears to be the exception. Those who repeatedly co-offend tend to share social and demographic characteristics, have more prior arrests, and offend with larger groups (Charette & Papachristos, 2017; McGloin et al., 2008). Without these shared characteristics, collaborations may be transient and transactional, relating to specific criminal opportunities. In addition, the *accomplice networks* of offenders can also contribute to group instability (Reiss, 1988; Sarnecki, 1990). Those with extended accomplice networks have, in principle, access to more criminal opportunities because more information about criminal opportunities flows through their direct and indirect contacts (Kleemans & De Poot, 2008). It is reasonable to assume that in these circumstances, it might be easier to form new co-offending groups and, at the same time, maintain existing ones since criminal opportunities arise through the information circulating in extended networks (Tremblay, 1993).

Co-offending groups' instability can also be attributed to decisions made throughout offenders' criminal careers. Preferences for solo offending or co-offending depend on offenders' criminal experience, the opportunities that arise, and the ability to find suitable accomplices (Reiss & Farrington, 1991; Reiss, 1988; Tremblay, 1993). Additionally, residential mobility, incapacitation through arrest or incarceration, and shifts to conventional careers may explain why some individuals temporarily stop co-offending or seek out new accomplices (Reiss, 1986).

While research has been conducted on co-offending groups, it is unclear to what extent co-offending groups tend to specialise in particular crime types. In the few studies published on the subject, it has been suggested that juvenile co-offenders tend to specialise, but the behaviours displayed by adult co-offenders are less clear. Based on data from the 1967 National Surveys of Youth in the USA, Warr (1996) found that juvenile co-offending groups specialise in auto theft, shoplifting, and robbery. Grund and Morselli (2017) reached a similar conclusion when analysing arrest data for all ages from Quebec (Canada) between 2003 and 2009. Of more than ten thousand pairs of co-offenders - or *dyads* - analysed, 47% specialised in only one crime type. They found that individual offenders who specialised throughout their criminal careers were also members of these highly specialised dyads. This finding suggests that individual specialisation drives dyadic specialisation: specialised solo offenders will keep executing the same type of crime when co-offending, indicating that the decision to co-offend restricts the kind of crime they will co-execute.

McGloin and Piquero (2010) examined criminal specialisation of co-offending networks[1] using data about juvenile offenders in Philadelphia recorded in 1987. At the individual level, it was suggested that the networks' structure might explain, in part, offenders' versatility/specialisation. They used the concept of *network redundancy* to compare the versatility of offenders. A redundant network is one in

[1]In technical terms, the networks studied were the egocentric subgraphs associated with each offender.

which the nodes (i.e., offenders) have a similar connectivity pattern (e.g., small isolated groups where every offender shares a connection). New information cannot enter these fully connected groups if there is a similar connectivity pattern, decreasing the chance of learning about new criminal opportunities (Wasserman & Faust, 1994). Conversely, offenders in a non-redundant network have different connectivity patterns, allowing them to access information from other parts of the network (Barabási, 2016). According to their findings, juvenile offenders who belong to less redundant networks commit different types of crimes. In contrast, those who belong to more redundant networks tend to specialise. McGloin and Piquero (2010) controlled for the number of accomplices the offenders were exposed to, suggesting that criminal versatility may be explained by the structure and connectivity patterns of co-offending networks rather than by the number of accomplices. They explained that the results should not be interpreted as network redundancy causing criminal specialisation: criminal specialisation and network formation might provide feedback to each other.

The review presented in this section indicates that very little is known about the behaviours displayed by adult co-offenders compared to what is known about juvenile co-offending groups. Interesting results have been found in the few studies about criminal specialisation; however, they also highlight significant gaps in co-offending research that need to be filled. These gaps are related to the lack of studies conducted outside a small set of countries that use recent data to understand the behaviours displayed by adult co-offending groups. Moreover, the absence of a shared definition of a 'co-offending group' and a systematic method to identify them represent a significant shortcoming of existing research. Without this definition, comparing the scarce evidence about adult co-offending groups risks being confounded by additional sources of variation between studies. In the studies reviewed above, different units of analysis were used, including co-offending dyads, co-offending networks, accomplices networks, or co-offending *circles* (Grund and Morselli (2017) used this concept to refer to subgroups within a co-offending network). Thus, this exploratory research proposes a definition of co-offending groups based on network-related concepts before analysing the tendency of adult co-offending groups to specialise in particular crime types.

7.4 Method

This section outlines the conceptualisation of co-offending used in this study and its representation in network terms. Following this, the key approaches and measures used in the study are introduced.

7.4.1 Group definition

A necessary first step in examining specialisation within co-offending groups is to define what constitutes a 'co-offending group'. In this work, the definition provided by Warr (1996) was used as a starting point, which states that whenever two or more individuals come together to execute a crime, they constitute a co-offending group. Then, the definition's scope was expanded to include individuals with a relevant role before, during, or after the execution of a crime, in line with Tremblay's (1993) definition. In this definition, the actions executed by individuals define the boundaries of a co-offending group: if two or more individuals commit a crime or have a relevant role in its commission, they will be considered part of the same co-offending group.

This basic definition excludes features commonly attributed to social groups, such as role structure, norms, and identity (Johnson, 2013). However, it aligns with other definitions proposed in the literature. For example, Yablonsky (1959), while analysing gangs in New York City, contended that social groups (or collectivities) lay in a continuum, with mobs and crowds on one side and highly organised groups on the other. Yablonsky (1959) argued that co-offending groups lie somewhere along this continuum since they do not resemble mobs or highly organised groups. Co-offending groups (or *near groups*, as Yablonsky called them) have ambiguous role definitions, a lack of consensus on norms or rules, and transient membership. In this definition, therefore, there are no requirements about the internal dynamics of a group: involvement in the execution of a crime is all that is required.

According to this definition, it is possible to identify a co-offending group by knowing who executed a crime and who played a meaningful role in its execution. One source of such information is data concerning criminal investigations conducted by law enforcement agencies, which record the details of criminal events and their participants. These records are, of course, subject to known limitations (Campana & Varese, 2020) (see also Chapter 4). Victims will not report all crimes, and law enforcement agencies will not investigate all reported crimes. Moreover, there is no guarantee that an investigation will identify all those who participated in a given crime, which is, to some extent, dependent on law enforcement agencies' allocation of resources to each investigation. Notwithstanding these limitations, official records are the only viable data source concerning co-offending at a large scale. They are used as the basis for almost all research on the topic. Furthermore, while they only reflect offences which come to the attention of law enforcement, it is precisely these offences that are the targets for prevention; law enforcement can do little about a crime that is not reported.[2]

7.4.2 Data

The participants of criminal events were identified using information concerning criminal investigations held by Colombia's Attorney General's Office (AGO). As described in Chapter 4, these investigations are typically initiated through victims' reports or police-led initiatives; not all investigations will necessarily involve an arrest, but all arrests will be associated with an investigation. This study relies on data relating to all closed and ongoing criminal investigations involving adult offenders in Colombia's capital, Bogota, between 1/1/2010 and 31/12/2018.[3] The final dataset contains information about 76,697 offenders involved in 35,604 investigations.

The AGO identifies criminal investigations through a unique code, and individual offenders are referred to by their (encrypted) national identity numbers. Each record in the dataset corresponds to a single offender's involvement in a particular criminal investigation; accordingly, two offenders jointly committing the same crime would result in two observations in the dataset, and each observation would share the investigation's identifier code. Under Colombian Criminal Law, offenders are classified as either *authors* or *participants*. Those responsible for carrying out the criminal act (i.e., chief perpetrators) fall into the first category, while the second category includes individuals who had an essential role before, during, or after the criminal act (e.g.,

[2]Increasing rates or reporting and detection are, of course, important goals, but are distinct issues to the ones examined here and beyond the scope of this research

[3]This time frame differs from that described in Chapter 4 due to computational limitations encountered when using the algorithm described below

accessories or those who encouraged the crime without participating). This work makes no distinction between these categories, as per the definition of *co-offending groups*.

The records specified the types of crime with which each investigation was concerned. In Colombian Criminal Law, criminal offences are classified based on the legal rights they intend to protect. For example, eight crime types protect private property: theft, robbery, extortion, and fraud. Similarly, this Law has multiple types of crimes to protect public health, such as trafficking controlled substances or facilitating the production of drugs. The crimes in the dataset were classified according to 17 crime types. It is worth noting that each investigation can include one or multiple crime types: for example, an investigation of a robbery in which the offender injured the victim could include two crime types - theft and assault. Each investigation was regarded as a single criminal event, and all the related crime types were included.

7.4.3 Network representation and analysis

The relationships between offenders and criminal events can be represented as a bipartite network. As described in Chapter 3, a bipartite network is one in which the nodes can be partitioned into two groups, and edges can only exist between nodes of different groups (Newman, 2018). Bipartite networks are commonly used for analysing relationships between two different types of entities, such as events and individuals (Wasserman & Faust, 1994). In this work, the two groups of nodes correspond to offenders and criminal events, and an edge is placed between each offender and the crimes they were involved in. Figure 7.1 presents an example of a bipartite network with six offenders (1-6) connected to three crime events (a-c).

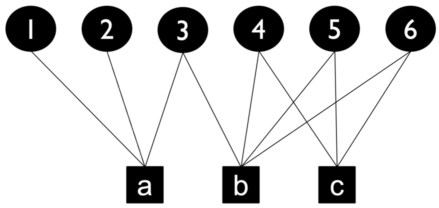


Figure 7.1: An example of a bipartite network with six offenders (1-6) connected to three criminal events (a-c).

As a first step in the analysis, it was necessary to identify co-offending groups in line with the proposed definition - i.e., offenders connected to the same crime event(s). In most studies, this is done by first taking the one-mode projection of the offender-event network to form a co-offending network containing offenders only. The one-mode projection is formed by retaining only one of the two groups of nodes (in this case, the offenders) and placing an edge between any two offenders connected to the same investigation in the original bipartite network. Once this network has been constructed, co-offending groups can be identified in several ways. The most straightforward approach is to identify the connected components in the network - i.e., groups of disconnected nodes. Alternatively, a more nuanced approach, which has been used in other studies (see, e.g., Bahulkar et al., 2018; Robinson & Scogings, 2018) is to apply community detection algorithms. These algorithms are designed to identify clusters of nodes that are densely connected to each other but have fewer connections to other nodes in the network (Newman, 2018). The *natural* division of the network into such communities might reveal coherent co-offending groups.

While these approaches have an intuitive appeal, using one-mode projection has significant limitations. In particular, the process results in the loss of information about the crimes associated with each edge, which means that it is not possible to take this information into account when identifying co-offending groups. In particular, it is not possible to say whether any two edges relate to the same or different crimes, which is critical to the definition of a group. Using structures detected in one-mode networks would bias the criminal specialisation analysis because it would be inconsistent with the definition of co-offending groups used here, which is based on joint participation in particular events.

An alternative approach, which overcomes this limitation, is to examine *maximal bicliques* in the original bipartite network. Bicliques are an extension of the concept of a *clique* in one-mode networks to the bipartite case. In a one-mode network, a clique is a set of nodes that are all directly connected to each other; that is, a complete subgraph (Barabási, 2016). Extending this idea to bipartite networks, a biclique is a set of offenders and events such that all offenders are connected to all events. A biclique is maximal if it does not belong to another biclique; i.e., no further offenders or events could be added. In practical terms, a maximal biclique represents the largest possible group of offenders and crimes such that all the offenders co-executed all the crimes. When identifying groups in this way, offenders' participation in crime events does not have to be assumed; it is directly depicted in the graph. Furthermore, using maximal bicliques provides refined information on who participated in which crimes, providing a better estimate of the criminal specialisation of groups.

In Figure 7.1, there are three maximal bicliques (i.e., co-offending groups): G'_1 ({1, 2, 3}, {a}), G'_2 ({3, 4, 5, 6}, {b}), and G'_3 ({4, 5, 6},{b, c}). A minimum number of events can also be set to consider only those groups involved in two or more crimes; G'_3 would be the only such biclique in this case. The Maximal Biclique Enumeration Algorithm (iMBEA) proposed by Zhang et al. (2014) was used to extract all the maximal bicliques in the network. The iMBEA combines backtracking [4] and branch-bound [5] techniques that reduce the search space of possible solutions, improving the efficiency in enumerating maximal bicliques in sparse networks such as the one examined here. This algorithm was implemented through the R package *Biclique* (Lu, Phillips, & Langston, 2020).

7.4.4 Measuring specialisation

The degree of specialisation of co-offending groups was measured using the *diversity index* proposed by Agresti and Agresti (1978). Multiple criminological studies have used it to gauge how much offenders specialise in specific crimes (e.g., Mazerolle et al., 2000; McGloin et al., 2007; Piquero et al., 1999). The offending diversity index d of a co-offending group i is given by the equation:

$$d_i = 1 - \sum_{m=1}^{M} p_m^2 \tag{7.1}$$

where p is the proportion of crimes committed in each of the M categories of crimes ($m = 1, 2, \ldots, M$). The minimum value of this index is

[4]The backtracking technique incrementally identifies solutions (i.e., maximal bicliques) while discarding those who fail to satisfy a condition (i.e., non-maximal bicliques). See (Van Beek, 2006).

[5]This method enumerates all the possible solutions (i.e., bicliques) and partitions them into disjoint sets that are represented as nodes in a branching tree. The algorithm explores the branching tree and evaluates each node (i.e., if it can be a maximal biclique). If the node is not a suitable candidate, it stops exploring the branches below this node, making it more efficient to search for possible solutions. See (Lawler & Wood, 1966)

$d_{min} = 0$, denoting a complete specialisation, and the maximum value is $d_{max} = 1 - \frac{1}{M}$, which is achieved when the proportions of crimes of each type are equal.

Given the lack of consensus about how to aggregate criminal offences when studying criminal specialisation (Mazerolle et al., 2000; Sullivan et al., 2006), the grouping strategy of crimes used here followed the classification used by Colombian Criminal Law. This law specifies seventeen types of crime (and therefore $d_{max} = 0.94$). The number of categories in which crimes were grouped is greater than those used in many previous studies, which have used between three and ten crime types (e.g., Horney, Osgood, & Marshall, 1995; Mazerolle et al., 2000; Piquero et al., 1999), though some examples have used a similar number (Sullivan, McGloin, Ray, & Caudy, 2009). Having a larger number of crime categories avoids introducing a bias while assessing the degree of specialisation through the choice of grouping strategy (Sullivan et al., 2006). However, a more granular crime classification will naturally lead to lower estimates of specialisation since pairs of crimes are less likely to be identified as belonging to the same type.

For this study, the lack of consensus in the academic literature regarding how to group crimes means there is little basis to deviate from the legal classification; hence, this was used for this study. Table 7.1 shows the distribution of crime across the investigations in which two or more co-offenders participated. It also shows the distribution of crimes per investigation. 56% of the investigations included a crime against private property. This crime also represented 40% of the total number of crimes observed in investigations linked to two or more offenders. The proportion of crimes against private property is consistent with findings reported elsewhere (see Chapter 2). Burglaries, robberies, thefts of cars, and minor thefts are usually associated with co-offending since they often require some level of collaboration between the offenders (Carrington, 2014; van Mastrigt & Farrington, 2009; van Mastrigt, 2017; van Mastrigt & Carrington, 2019).

Table 7.1: For all investigations linked to two or more offenders, the (a) proportion of investigations involving each crime type, and (b) proportion of this crime type as a portion of all crimes. For example, 56% of the investigations included a crime against private property. This type of crime represented 40% of the crimes observed in the dataset.

	(a)	(b)
Property	0.56	0.40
Public safety	0.25	0.21
Public health	0.15	0.12
Public administration	0.12	0.09
Personal integrity	0.11	0.07
Others	0.24	0.11

As an example, if Group A is linked to two criminal investigations - one for a drug-related crime and the second investigation for another drug-related crime and assault, then the d index will be calculated as follows

$$\begin{aligned} d_A &= 1 - [(\tfrac{2}{3})^2_{drugs} + (\tfrac{1}{3})^2_{assault} + ... + 0^2] \\ &= 1 - \tfrac{5}{9} \\ &= \tfrac{4}{9} \end{aligned}$$

Note that $[...0^2]$ represents the 15 crime types in which this group did not participate. Given their d index, Group A would be considered neither a specialist nor a generalist. In another example, Group B is linked to three investigations: investigation 1 (a drug-related crime), investigation 2 (a drug-related crime), and investigation 3 (a drug-related crime and burglary). The d index for this group would be estimated as shown below. Accordingly, Group B would be considered more specialised than Group A, as $\frac{3}{8}$ is closer to 0.

$$\begin{aligned} d_B &= 1 - [(\tfrac{3}{4})^2_{drugs} + (\tfrac{1}{4})^2_{assault} + ... + 0^2] \\ &= 1 - \tfrac{5}{8} \\ &= \tfrac{3}{8} \end{aligned}$$

Previous studies have addressed the limitations of the diversity index. As noted by Sullivan et al. (2006), for example, the range of possible values of d for any particular group is dependent on the number of offences committed: if a group committed only 2 offences, for example, the maximum possible value of d is 0.5. Furthermore, this value is lower than that for a group committing 3 offences of different types (0.66), even though in both cases, the offending is as diverse as it possibly can be. For this reason, some authors standardise d according to the maximum value that could be achieved (which would give $d = 1$ in both aforementioned cases) (e.g., Grund & Morselli, 2017). Standardisation is not followed here based on the rationale that diversity is not independent of offence frequency: 3 offences of 3 different types represent more significant evidence of diversity in some sense than 2 offences of 2 different types. In any case, the magnitude of non-zero values of d is of relatively little consequence since the primary focus for analysis is on the distinction between zero and non-zero values. A further feature of the diversity index is that, unlike other methods of measuring offending specialisation, it does not consider the sequence in which co-offending groups committed the crimes. The groups are compared based on all the crimes detected by the AGO and not only through the sequence of crimes they executed.

7.5 Results and discussion

The bipartite co-offending network contained information about 76,697 adult offenders linked to 35,604 investigations. The iMBEA algorithm enumerated 29,195 bicliques with at least two co-offenders connected to a minimum of one event. 93% of the co-offending groups (27,399) were only linked to one event, meaning that they did not re-offend after the AGO recorded the first investigation during the study period. The remaining 7% (1,796) re-offended and associated with more than one investigation. Figure 7.2 presents the distribution of the sizes of bicliques with at least two co-offenders linked to a minimum of two events. Of those bicliques, 1,021 had two offenders involved in two criminal events, and only 36 (2%) were involved in more than four crimes. The proportion of groups that committed more than two crimes is small compared to the number of groups that the algorithm enumerated. However, this proportion is relevant considering the number of offenders and investigations; these bicliques included 4,857 distinct offenders connected to 3,875 investigations.

Regarding the proportion of offenders shared among bicliques, 14% (691) of the offenders from re-offending groups belonged to more than one group. On average, offenders in this subset were part of two co-offending groups, and 32% (587) of the bicliques had at least one offender in common with another group. These figures suggest that, although co-offending groups had some overlap, its extent was minimal. They also indicate that adult co-offending groups behaved similarly to juvenile groups, as criminal partnerships were limited to a few events (Carrington, 2002; McGloin & Piquero, 2010; McGloin & Thomas, 2016;

Reiss & Farrington, 1991; Weerman, 2003, 2014; Warr, 2002, 1996; van Mastrigt, 2017). However, the truncated nature of the data should be considered when interpreting this finding. The data used here represents a snapshot of the offenders' criminal careers in a single city. It is not possible to exclude the possibility that some groups committed additional crimes before the study window (e.g. only a portion of prolific relationships that started before 2008 is observed through the data used in this study) or that initial contact with the criminal justice system has caused these groups to improve their tactics. For example, co-offending in a different city could be among the decisions adopted by co-offenders to avoid detection. This alternative could not be explored with the data at hand.

Table 7.2: A cross-tabulation showing the number of bicliques according to the number of offenders and criminal events.

		Number of offenders				
		2	**3-5**	**6-10**	**11-20**	**>20**
Criminal events	**2**	1021	372	107	64	7
	3	140	39	12	9	0
	4	24	7	0	0	0
	5	3	1	0	0	0
	6	1	0	0	0	0

Regarding the central question of this study, Figure 7.2 shows the distribution of d for groups linked to at least two events. Of these groups, 54% (977) had an index equal to 0, denoting complete specialisation. Of these specialised groups, 77% had two offenders, 12% had three, and 5% had four offenders. The remaining 6% had between five and thirty-six offenders. 46% of the co-offending groups were non-specialists, with 27% having a d index between 0.4 and 0.5.

To meaningfully interpret the observed level of specialisation, it must be placed in context - in particular, it is necessary to compare it to that which would be expected in the absence of any effect. Since some degree of specialisation (i.e., repeated offending of the same crime type) would be expected purely by chance, the extent of the effect can only be established by comparing the observed level to a suitable null model.

To do this, alternative scenarios were simulated in which the crime types executed by each co-offending group were randomly selected in proportions reflecting the overall distribution of crime types. This represents a situation where the crime types associated with each group are independent, as would be the case if no specialisation effect was present. Having simulated this scenario, the resulting values of d can be calculated and compared with those for the observed data. If there was no specialisation effect in the data, the proportion of groups showing complete specialisation ($d = 0$) should be expected to align with the corresponding proportion for the randomised data.

One thousand simulations were completed: each iteration kept the original number of bicliques (that is, 1,796 groups that re-offended), offenders per biclique, criminal investigations, and crime types per investigation. The types of crimes for each investigation were randomly assigned using a weighted probability to follow the original distribution of crimes observed in the data. Across all iterations, the maximum proportion of co-offending groups with $d = 0$ was 18%. The proportion of specialised groups in the original data was 54%, and so the observed data is entirely inconsistent with this null model. Accordingly, the proportion of highly specialised groups was not observed by chance.

Table 7.3 shows the distribution of crime types committed by specialised ($d = 0$) and non-specialised groups ($d \neq 0$). 61% of the crimes committed by highly-specialised groups involved crimes against private property. Nearly 20% of the investigations were related to crimes affecting public safety (e.g., illegal firearms possession or participation in the criminal activities of organised crime groups) and people's integrity (e.g., assault). The distribution was different for non-specialised groups. 29% of the crimes committed by non-specialised groups were related to public safety and 25% against private property. The findings imply that specialisation is associated with property crime to some extent. One possible explanation for this is that since property crime often involves specific skills (e.g. burglary), it is likely to be committed repeatedly by groups with the expertise and not by those who do not. On the other hand, public safety offences are more likely to appear as part of a general pattern of offending.

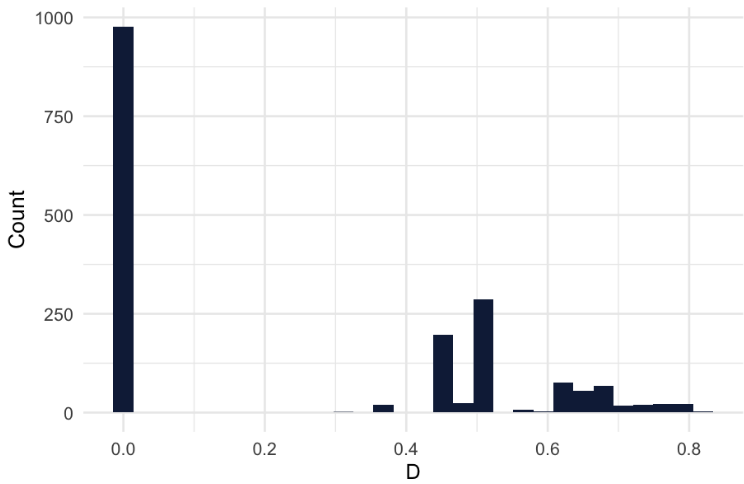


Figure 7.2: A histogram showing d's distribution. 54% (977) of the co-offending groups were highly specialised ($d = 0$). For non-specialised groups, d ranged between 0.32 and 0.82. 27% (485) had a d-index between 0.4 and 0.6.

The results obtained here were compared with those reported by Grund and Morselli (2017) by considering the bicliques with two co-offenders. In Grund and Morselli's work, the units of analysis were

Table 7.3: Distribution of crimes committed by specialised (d = 0) and non-specialised co-offending groups (d$\neq$0).

	Proportion	
Crime type	Specialised	Non-Specialised
Private property	0.6	0.25
Public health	0.1	0.1
Personal integrity	0.09	0.07
Public safety	0.07	0.28
Public Admin	0.06	0.11
Other	0.08	0.19

the dyads in the one-mode projection of the network, and specialisation was measured by considering all crimes on which they had collaborated (including those committed as part of a larger group). The correspondence with two-offender bicliques is not exact - some dyads may not appear as bicliques (if all their offences involved a particular 3rd offender), and some bicliques may not include all offences committed by the pair (since some may have been committed as part of other groups). Nevertheless, there is likely to be a large degree of overlap between the concepts. Grund and Morselli observed that 47% of dyads were completely specialised. The results presented here show that a higher proportion of two-offender bicliques, 64%, were specialised (see Figure 7.3). Similar to what was noted above, bicliques with two co-offenders who showed specialisation in the data were mainly related to crimes against private property (see Table 7.4) (Grund and Morselli (2017) did not include a precise description of the types of crimes executed by highly-specialised dyads). As described by Sullivan et al. (2006), the grouping strategy of crimes directly impacts d's distribution; hence, comparing both studies is not straightforward. However, it is possible to observe that roughly half of the groups had some degree of criminal specialisation, showing some degree of specialisation in co-offending.

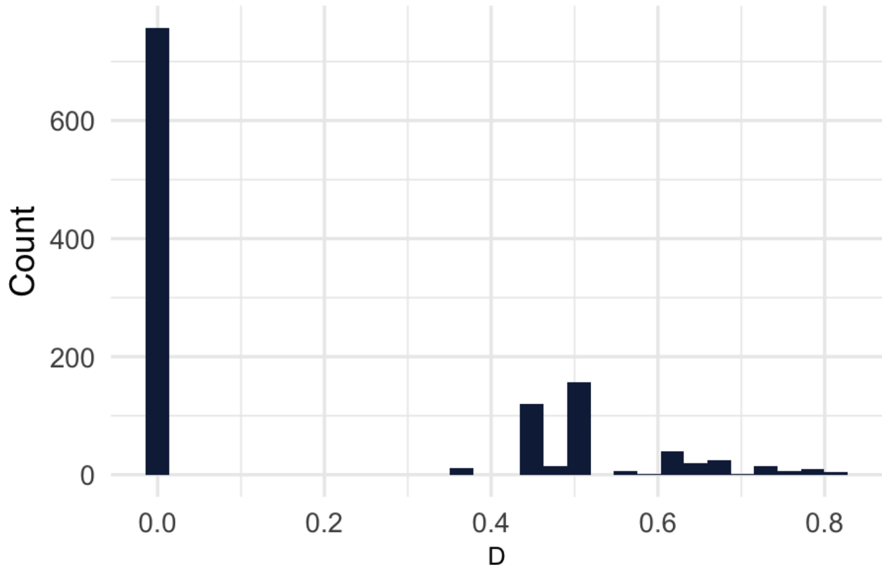


Figure 7.3: A histogram showing d's distribution in bicliques with two offenders. 64 per cent (761) were highly specialised ($d = 0$) dyads.

Table 7.4: Distribution of crime of specialised co-offending groups (d = 0) with two co-offenders.

Crime type	Proportion
Private property	0.68
Personal integrity	0.09
Public health	0.08
Public administration	0.06
Public safety	0.05
Others	0.04

The time course of activity by co-offending groups was also analysed during the study period to see if there were differences between specialised and non-specialised groups. To this end, the timestamps attached to each criminal investigation were used. These stamps indicate the date the AGO started investigating a particular event. It was assumed that these dates represented the date the co-offending group committed the crimes. Similar to what was done above, groups were divided between specialists ($d = 0$) and non-specialists ($d \neq 0$), and the number of days between the first and last crime recorded for each group was measured, representing the extent of observed offending. The number of investigations per group was considered to see if the number of investigations could explain any differences between these groups, but they were found to be similar. On average, specialised groups participated in 2.09 events, while non-specialised groups in 2.23.

Figure 7.4 presents the distribution of intervals (days) between the first and last crime event. The mean number of days between the first and last crime recorded for highly-specialised and non-specialised groups are 395 and 544, respectively. Likewise, the median intervals are 194 days for highly specialised groups and 402 for non-specialised groups. The Mann-Whitney U test suggests the medians are statistically different ($W = 320220$, $p < 0.001$). Hence, specialised groups executed their crimes in a shorter time than non-specialised groups. These differences might be attributed to the *spurts of specialisation* displayed by offenders throughout their criminal careers (e.g., Deane et al., 2005; Sullivan et al., 2006; McGloin et al., 2007; Steffensmeier & Ulmer, 2017; Shover, 2018). If offenders display such spurts, they execute crimes of the same type for a short time before executing crimes of a different sort, even when co-offending. A hypothesis that should be tested in future work, using a larger time frame, is that co-offending groups also display spurts of specialisation. A larger time frame makes it possible to understand better the behaviours exhibited by co-offending groups. The truncated nature of the data might not reveal the spurts of specialisation exhibited by the groups considered in this study as non-specialised.

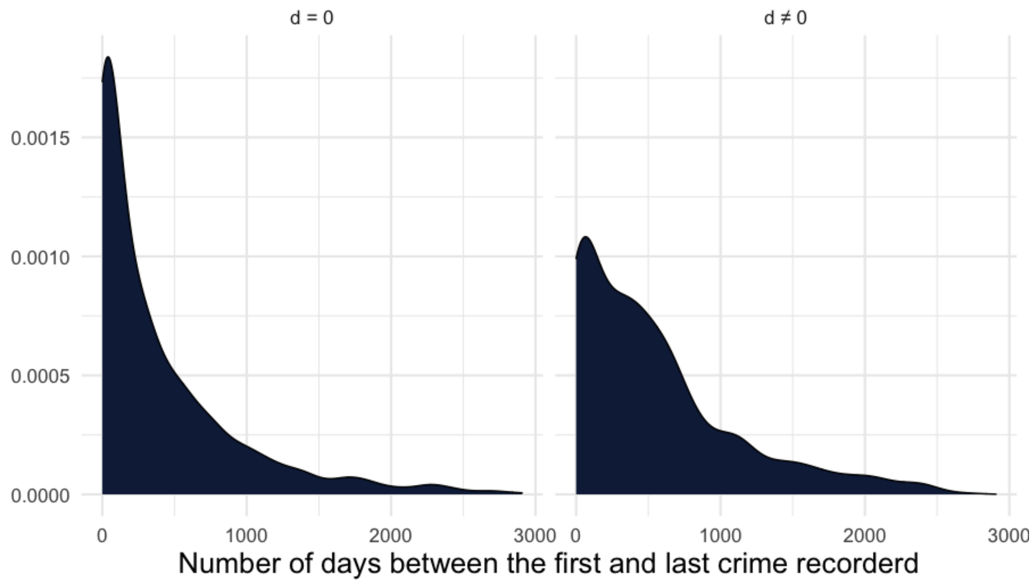


Figure 7.4: Density plots showing the distribution of days between the first and last crime recorded for highly specialised groups (left) and non-specialised groups (right).

7.6 Conclusions

The work presented here contributes to the scarce literature on the criminal specialisation of co-offending groups. Official records were used to build a bipartite network connecting offenders with criminal events and extracted maximal bicliques to represent co-offending groups. Based on the d diversity index, this exploratory research showed that more than half of the groups participating in at least two criminal events were highly specialised. A simulation analysis made it possible to conclude that the proportion of highly specialised groups was not observed by chance. Differences in the distribution of crime types between specialised and non-specialised groups and the time these groups remained active were also reported here.

To the best of the author's knowledge, this research is the first to study specialisation for co-offending groups defined in a general sense: others have studied either egocentric networks (McGloin & Piquero, 2010) or dyads (Grund & Morselli, 2017). Here, co-offending groups could take any form and were defined explicitly by their involvement in criminal events. These findings suggest that re-offending groups display a high degree of specialisation in much the same way as individual offenders do. This potentially supports theories which suggest that co-offending relationships arise in shared environments and has natural applications for prevention.

Direct comparison with the level of specialisation observed in other studies (including those concerned with individual offenders) is problematic for several reasons. The most immediate is that few studies report their findings in the same terms as shown here: in many studies, only the mean of the diversity index is reported, which - given its bimodal nature - masks essential features. More fundamentally, however, the lack of consistency in crime categories and data sources means that quantitative comparison would be of only limited value. Establishing correspondence across settings is an ongoing challenge for crime science. The most immediate comparison for this study is that of Grund and Morselli (2017), who found a similar but slightly lower level of specialisation; again, the studies are not directly comparable.

One question for further work concerns the extent to which the group-level specialisation observed is a by-product of the individual-level specialisation of group members. Grund and Morselli (2017) found that specialisation at the dyadic level was similar to, or even less than, that which would be expected based on individual-level specialisation. If this was the case for groups, it would suggest that specialisation at the group level was simply an artefact of members' characteristics, in line with the idea of local norms. If, on the other hand, group specialisation was beyond what would be expected, it might suggest that groups actively come together to commit particular crime types.

Although comprehensive in terms of the type of investigations included (both open and closed), the time frame (eight years) and the types of crimes included (all possible crimes), the data set lacked information on the offenders' level. The availability of geographic (e.g., where crimes were committed or where offenders reside) and socio-demographic data (e.g., age, ethnicity, or prior arrests) in future work could help hypothesise about the drivers behind the decisions of co-offenders (Charette & Papachristos, 2017; McGloin et al., 2008). For example, it would be interesting to examine differences between three classes of co-offending groups - i.e., those who ceased after the first investigation was recorded, those who re-offended and executed the same crime, and those who explored a new crime down the road. One potential hypothesis is that having contact with the criminal justice system discourages co-offenders from keeping the same accomplice. The data showed that 20% (13,041) of the co-offenders who were part of a co-offending group that committed a single crime were involved in new crimes after the one executed with the co-offending group. A considerable proportion of offenders was not included in a subsequent investigation, supporting this previous hypothesis.

Future research could also examine the differences between specialists and generalist groups and assess how these differences might explain the decisions to commit the same crime or try a new one. It is possible to assume that the decision to re-offend with the same accomplice follows a similar rational process as when offenders choose an accomplice for the first time (van Mastrigt, 2017) (see also Chapter 2). Co-offenders will re-evaluate their accomplices after the initial crime and stick with the same partner if finding a new accomplice is costly. The availability of crime opportunities could also be significant in this re-assessment. If more opportunities at hand match the combined criminal capital of the co-offending group, then it will be more likely to see the formation of specialised groups. Incipient co-offending groups will grab 'low-hanging fruits' if these opportunities are evident (e.g., offenders exploiting a scam that has proven to work). A similar rationale could explain why some groups become generalists. The evaluation might centre around accomplices' willingness to offend rather than their specific skill set. Some crimes depend on offenders' ability to find motivated accomplices Tremblay (1993). Hence, individuals' disposition to offend will be sufficient to stick with the same partner, even if this decision implies exploring new crimes. Again, these considerations should factor into the role detection and contact with the criminal justice system might have in groups' subsequent decisions.

This study faced some limitations related to the data type (Humphrey & Gibbs Van Brunschot, 2021). As discussed in Chapter 4, due to the data's nature, failed co-offending relationships were included - i.e., co-offending groups whose primary objective of avoiding detection was not achieved. Hence, it was not possible to analyse co-offending groups that remained undetected in this particular city. This data is also subject to the inherent limitations prosecutors face. The AGO can fail to uncover all the events' participants or to record and investigate all the criminal events in this city during the study period. This data is also subject to biases derived from disproportionate attention to specific offenders or budget limitations (Campana & Varese, 2020). Despite these limitations, official records such as the ones used here remain among the few sources of information that can shed some light on activities that, by definition, try to stay covert.

This study aligns with current efforts to exploit network-related concepts to answer crime-related questions (Papachristos, 2011; Bichler, 2019). Here, maximal bicliques were used for the first time as an alternative to identify co-offending groups in a sizeable bipartite network linking offenders and criminal events. A relatively large body of studies using network science to analyse covert networks have relied on one-mode networks to study the behaviours these networks display. This research has demonstrated that studying bipartite networks directly is also a suitable alternative to extract meaningful insights to help analyse the behaviours displayed by these networks, contributing to one of the goals of this thesis, as discussed in the Introduction.

Practitioners would find the analytical strategy employed here helpful because it shows how to extract insights from official records. These insights could help law enforcement agencies decide how to deploy their limited resources. These agencies might want to gauge the number of co-offending groups operating in a meaningful geographical unit and determine if these groups specialise in crimes causing harm to society (Sherman, Neyroud, & Neyroud, 2016). Priorities could be set by identifying such groups and understanding their behaviours. The proposed analysis could be enriched by including geographical information. Adding this geographical information to the identification of co-offending groups could reveal co-offending groups' hot spots. This information could also be exploited to try to identify the settings used by offenders to meet and plan the execution of crimes (Felson (2003) referred to these places as *offender convergence settings*). See further discussion in Chapter 8.

Chapter 8

Summary, Discussion, and Future Work

8.1 Overview

This thesis aimed to explore different features of co-offending using the concepts and tools developed in network science and criminology. In Chapter 5, the extent to which co-offending networks exhibited triadic closure was studied using a method specifically tailored to the bipartite nature of the data. Chapter 6 looked into the accomplice selection process by testing four network-growth mechanisms in three co-offending networks. The study presented in Chapter 7 had a different aim: instead of delving into accomplice selection, it proposed a new way to identify co-offending groups by enumerating substructures (i.e., bicliques) in networks modelling connectivity patterns between offenders and criminal events. Assessing the tendency to which co-offending groups specialise in specific crimes was possible by identifying these meaningful substructures.

This concluding Chapter summarises these studies and discusses the unifying themes observed across this thesis. Future research paths for crime researchers are laid, suggesting alternatives to further understanding the behaviours co-offending networks exhibit.

8.2 Summary

Chapter 5 analysed triadic closure in co-offending networks - i.e., the tendency of two offenders to co-execute a crime when they have an accomplice in common. Triadic closure - which in general refers to a tendency for individuals who share common neighbours also to be linked themselves - is commonly observed in social networks and has been reported for some co-offending networks (e.g., Iwanski & Frank, 2013; Bright et al., 2020). However, an analysis of this trait in light of the accomplice selection theories was missing. Hence, this thesis argued that current theories about accomplice selection do not directly address (or reject) the idea of *transitive* relationships between offenders (transitive relationships is another way used to describe triadic closure). Despite not addressing transitivity directly, these theories share three elements that may have implications for triadic closure in co-offending networks. These elements are the trust that emerges when two unconnected individuals share a connection (e.g., two unconnected offenders that share an accomplice), the limitations posed by geographic conditions (e.g., propinquity), and homophily. Each of these suggests that co-offending networks are likely to display triadic closure.

The data described in Chapter 4 was partitioned into twelve rolling-temporal windows of three-year duration. Bipartite networks were created to model the connections between offenders and criminal investigations in each temporal window. The degree of transitivity in co-offending relationships was measured in these bipartite networks.

The results indicate that the probability of observing a co-offending relationship between two accomplices of a given offender ranged between 3% and 53%. These numbers suggest that co-offending networks exhibit some transitivity like other social networks. The patterns of prior interactions observed in co-offending networks, as in other social networks, might affect the decisions made by offenders when selecting new accomplices. The results are consistent with theories about accomplice selection encompassing mechanisms of trust, geographical proximity, and homophily.

Chapter 5 also addressed two methodological concerns. Numerous studies in networked criminology have relied on one-mode networks (derived via the projection of two-mode networks) to study the properties of crime-related networks in general and co-offending networks in particular. However, using projected one-mode networks can result in triadic closure being overestimated. When projecting a two-mode network into a one-mode network, a single event can create multiple edges between offenders (Opsahl, 2013); specifically, the projection produces numerous cliques, increasing the clustering co-coefficient. Because many of the present triangles result from the same event, they do not represent triadic closure in the sense predicted by theory. Therefore, triadic closure needed to be measured in the original two-mode networks to avoid introducing a bias when estimating this coefficient. Accordingly, triadic closure was measured using a method that counts paths of length 4 in the bipartite network and considers whether these paths are open or closed. Closed paths of length 4 represent triads: two offenders, who share an accomplice, executing a crime (i.e., *genuine* transitive relationships) - see Figure 5.3. The modified clustering coefficient is equal to the ratio of closed paths of length four to the total number of closed and opened paths of the same length. Comparing the coefficients measured in the one-mode and bipartite networks revealed that those observed in the former were relatively high, ranging between 0.92 and 0.98. In contrast, the coefficients in bipartite networks ranged between 0.02 and 0.53. This illustrates the earlier point about how triadic closure can be overestimated when using one-mode projections.

The second methodological concern was the possibility of observing the values of the clustering coefficients by chance. Accordingly, this Chapter compared the observed coefficients with those obtained under the null hypothesis that offenders randomly created co-offending relationships, reducing the chances of observing transitive relationships. The distribution of the clustering coefficients under the null hypothesis was obtained by randomly re-wiring the original bipartite networks while preserving the original number of offenders, events, and connections they had. The observed coefficients were at the extreme end of the distribution under the null hypothesis in each temporal window, indicating that the coefficients measured in the original networks were not obtained by chance. This type of analysis is common in other disciplines using networks to model the interaction between heterogeneous entities; however, few studies have used this approach in criminology to assess the statistical significance of network-related statistics in general and clustering coefficients in particular.

Chapter 6 expanded the scope of the analysis by testing four mechanisms that represent potential explanations for how offenders choose their accomplices; or, equivalently, for how co-offending networks evolve and grow. These mechanisms are *popularity* (i.e., offenders execute crimes with those that have previously co-offended with numerous accomplices), *reciprocity* (i.e., offenders recruit former recruiters to execute new crimes), *reinforcement* (i.e., offenders re-offend with former accomplices), and *triadic closure* (i.e., offenders co-offend with the accomplices of their accomplices).

The methodological approach for this Chapter was different. Temporal information - specifically the date on which the Prosecution Office opened an investigation (this date was assumed to be the date on which offenders executed the crime) - was used to continuously observe the evolution of three networks components with 4,286, 227, and 211 offenders. In this way, the sequence in which co-offending links were formed could be observed. Using this information, a discrete choice model was used to study the evolution of these networks. A discrete choice model of network formation views network evolution as the result of discrete choices made by offenders when selecting their accomplices (i.e., forming new links in the network). In tandem with conditional logistic models, this approach compares the characteristics of those accomplices who were selected to those that were not and allows their potential influence on the choice to be quantified. In this way, it was possible to understand if accomplices' network-related characteristics (e.g., the number of previous accomplices an offender had) were favoured (or not) when offenders selected accomplices. The outcomes of the conditional logistic models suggest which mechanism(s) are better suited to describe the behaviours displayed by the networks. Randomisation procedures were also used to overcome data limitations (e.g., the lack of information about who selected whom for each link).

The results indicated that the networks displayed different behaviours when evolving, and these behaviours could be explained through a combination of network growth mechanisms. It also provided evidence about the lack of predictive power popularity in explaining how co-offending networks evolve. The largest network consistently yielded negative, statistically significant coefficients for this mechanism, suggesting that having more connections (i.e., more previous accomplices) reduces the chances of being selected. This result contradicts previous theories about the critical role of prolific co-offenders in creating co-offending networks. Reinforcement yielded both negative and positive statistically significant coefficients. The mixed results suggest that some offenders are willing to re-offend with the same accomplices, while others will avoid re-offending with the same person down the road. Reciprocity also yielded mixed outcomes. Accordingly, selection (or recruitment) might operate in two ways. It can bring together offenders through interactions of the sort 'A selects B' followed by 'B selects A'. It can also be a repellent between accomplices as offenders avoid re-offending with known associates. Lastly, triadic closure delivered positive statistically significant coefficients, suggesting that previous accomplices might have a vital role when procuring accomplices (a result similar to that reported in Chapter 5).

Chapters 5 and 6 looked into the accomplice selection process using concepts and tools developed in network science. Chapter 7 also relied on such tools to identify co-offending groups in co-offending networks and assess their degree of specialisation using the *diversity index*. Maximal bicliques were used to identify co-offending groups in a bipartite network modelling the interaction between offenders (76,697) and criminal events (35,604). As explained in Chapters 3 and 7, maximal bicliques are subgraphs in which all the nodes share a connection - i.e., a subset of offenders and a subset of events, where all offenders are connected to all events. A maximal biclique represents the largest possible set of offenders and crimes such that all the offenders co-executed all the crimes. The idea of maximal bicliques aligns with the definition of co-offending groups: people coming together to co-execute crimes create co-offending groups.

A recently developed algorithm was used to enumerate the bicliques in this network (Zhang et al., 2014). In total, 29,195 bicliques with at least two co-offenders were identified. A small proportion of these bicliques (1,796) were observed to have committed more than one crime (i.e., the same offenders executed a second crime together). Despite representing a small proportion of the overall population, they encompass numerous offenders (4,857) and investigations (3,875). Moreover, 57% (1,021) of the re-offending groups comprised two co-offenders linked to two events.

The d index provided a measure of co-offending groups' tendency to become specialists (or generalists). Of those groups that re-offended, 54% had a d index equal to 0, indicating complete specialisation. Over 60% of the criminal events in which highly-specialised groups participated were related to crimes against private property (e.g., theft, burglary, fraud). The other 46% of the re-offending bicliques had a d index greater than 0, suggesting they were not completely specialised. These bicliques were linked to crimes against private property, public safety (e.g., arms trafficking, organised crime, possession of weapons that can only be used by the armed forces), and public administration (e.g., impersonation of authorities, procedural fraud, embezzlement of public property).

This Chapter included a simulation analysis to assess the significance of the results by comparing the results observed in this analysis with those obtained under a null hypothesis in which co-offending groups randomly selected the crimes. This analysis consisted of 1,000 simulations in which the crime types were randomly assigned while preserving the original distribution of crime types. The d index was calculated in each iteration to see the proportion of specialised and non-specialised groups. The highest proportion of completely specialised groups seen in a single iteration was eighteen, indicating that the observed proportion (54%) is at the extreme end of the distribution of the null model. Accordingly, it is with high confidence that the proportion of specialised groups in the original data set was not observed by chance. Additional analysis was completed to identify the difference between specialised and non-specialised groups. Specialised groups executed the crimes in a shorter time frame than non-specialised groups (the median period between the first and last crime recorded was 194 days for highly-specialised groups and 402 days for non-specialised groups). This finding could be related to the spurts of specialisation offenders show throughout their criminal careers. However, more research is needed to understand how solo offending and co-offending shape criminal careers and determine if co-offending groups also exhibit specialisation spurts similar to solo offenders.

In short, Chapter 7's contributions were two-fold. First, it proposed a new way to identify co-offending groups by enumerating maximal bicliques in bipartite networks. Second, it provided evidence about the degree of criminal specialisation of adult co-offending groups, a subject that has not received much attention in the literature.

Three unifying themes were identified throughout the completion of this thesis. The first theme relates to the possibility of studying accomplice selection through networks. The second concerns the insights law enforcement might find helpful in preventing crime. The third theme considers the value of using bipartite networks to study co-offending.

8.3 Studying Accomplice Selection Through Networks

Using networks to examine co-offender connections provides a specific terminology and technical apparatus to study theoretical mechanisms. As discussed in Chapter 2, several accomplice selection theories have been proposed. However, they are often expressed in qualitative terms, and it is not clear how to test them in a rigorous empirical way. Representing these decisions as a network, and translating the theories into network terms, provide a means to achieve this end. In this regard, Chapters 5 and 6 examined the correspondence between four network growth mechanisms and theoretical accomplice selection processes proposed in the literature. These similarities and differences were identified, as summarised in Table 8.1. Given these connections, the analysis presented in these two chapters constituted an examination of the validity, or predictive power, of these theoretical processes. In this way, their findings add some evidence to the 'theory of networked opportunity' proposed by Bichler (2019). Rule No. 6 of this theory posits that individuals' perceptions and decisions to engage in criminal activities are mediated by the information and resources circulating in their social networks. Some of the behaviours exhibited by the networks exemplify this principle. The fact that networks display triadic closure, for example, shows that the configuration of existing relationships influences the formation of new collaborations. No attempts were made here to distinguish between triadic closure's underlying mechanisms - i.e., trust, offenders' spatial convergence in specific settings, or homophily - due to the limitation posed by the data retrieved from the AGO (see Chapter 4 for a discussion about the data's limitations). However, each of these arguments aligns closely with the idea that information and resources play a key role in drawing offenders together.

Moreover, the results in Chapter 6 suggest that multiple network growth mechanisms (i.e., popularity, reinforcement, and reciprocity) might explain how offenders select their accomplices. These mechanisms could explain some of the behaviours exhibited by co-offending networks, indicating that corresponding theories presented in Table 8.1 could explain the formation of co-offending relationships. As mentioned, additional network-related mechanisms could be included in the analysis to gain further insights into the evolution of co-offending networks. Including such mechanisms represents an avenue for future research. In some cases, this possibility for future work depends on the availability of more nuanced data about the offenders and the crimes they committed (e.g., offenders' sociodemographic variables and geographical information about the offenders and crimes - i.e., offenders' residences and the locations where crimes were committed).

Accordingly, modelling co-offending relationships through networks and analysing the behaviours they display can help crime researchers better understand accomplice selection processes. This thesis takes the first step to formulate a 'networked accomplice selection theory' by identifying the similarities and differences between accomplice selection theories and network growth mechanisms and describing a methodological framework to analyse the temporal evolution of co-offending networks. More analysis of various co-offending networks and the inclusion of more mechanisms are needed to develop this theory more comprehensively. Ultimately, this theory should explain *why* co-offender A chooses co-offender B. Accordingly, it should consider how co-offending networks shape offenders' decision-making

Table 8.1: Shared aspects between network growth mechanisms and accomplice selection processes

Network Growth Mechanisms	**Aspects Shared with Accomplice Selection Theories**
Triadic Closure	- Trust plays a vital role in explaining accomplice selection (Tremblay, 1993). - Former accomplices become a direct source of information about potential accomplices, their trustworthiness, and their criminal capital or reputation (von Lampe & Johansen, 2004) - Co-offenders sharing the same social foci (i.e., convergence settings) are more likely to co-offend (Felson, 2003) - Co-offending relationships are likely to be homophilic (Weerman, 2003). This can be due the underlying distribution of social characteristics (Van Mastrigt & Carrington, 2014)
Popularity	- Individuals are more likely to be chosen as accomplices if they already have multiple co-offending connections (Sarnecki, 2001) - Popularity may be attractive in itself; existing co-offending relationships may be seen as a form of endorsement - Individuals become popular due to their aptitude for crime and criminal capital (McCarthy et al., 1998; McCarthy & Hagan, 2001; Hochstetler, 2014) - Popular offenders might be unattractive to potential accomplices because popularity increases visibility and the risk of being arrested (Morselli, 2009)
Reinforcement / Reciprocity	- Offenders do not have fixed roles throughout their criminal careers; they alternate between the roles of 'recruiters' and 'followers' (Van Mastrigt & Farrington, 2011) - Trust builds among those who co-execute a crime (Charette & Papachristos, 2017), allowing them to stick together down the road - Reinforcing existing relationships might be expected from a rational decision standpoint; it might help reduce the costs of finding new accomplices with the same criminal capital - However, numerous studies show that offenders are more likely to co-offend with new accomplices rather than with known associates (e.g., Weerman, 2003; Warr, 1996; McGloin & Thomas, 2016).

processes when selecting accomplices. Apart from considering personal traits (e.g., age, criminal history, and sex), this theory should also consider the embeddedness of individuals in wider social environments to understand, for example, how roles, expectations, and pressures conducive to criminality emerge in their social milieu. By considering the embeddedness of offenders in broader social contexts, this theory could also explain (if any) context variations in accomplice selection processes (e.g., co-offending selection in high-income countries v. low and middle-income countries or accomplice selection in highly-populated areas v. low-density areas).

8.4 Insights for Law Enforcement Agencies (LEAs)

How can LEAs disrupt co-offending networks to prevent crime? Unfortunately, this question has not received much attention. Carley, Lee, and Krackhardt (2002) defined network disruption as the actions intended to reduce the rate at which information flows within a network and diminish the ability to execute specific actions. In the context of co-offending networks, disruption can be understood as the actions oriented to prevent the creation of new co-offending relationships (i.e., stop networks from growing). Studying the evolution of co-offending networks and identifying the mechanisms that drive their growth can provide some insights into disruption strategies. For example, suppose LEAs determine that triadic closure explains how a particular co-offending network evolves. In that case, LEAs might seek to identify the locations where motivated offenders converge to plan or act upon criminal opportunities. As suggested by Felson (2003), crime can be prevented by increasing the difficulty of finding suitable partners. For example, patrolling public areas (e.g., parks) where potential accomplices meet can potentially reduce crime by simply not letting motivated offenders find each other.

Similarly, suppose popularity strongly predicts how another co-offending network grows. In that case, LEAs might target individuals acting as hubs (i.e., well-connected offenders) and seek to understand why these individuals attract new accomplices. These hubs might, for example, have a greater *social capital* compared to those less connected offenders (Sparrow, 1991). In the scenario of co-offending, the social capital of those well-connected offenders would be in the form of information about crime-related opportunities, skills, a large appetite for crime, details of those individuals that have offended in the past and that might want to participate in new criminal ventures, and insights about the specific skills possessed by those with whom they have co-offended in the past. Alternatively, hubs could also be those prone to participate in criminal activities, like the go-to person when someone needs additional help when committing a crime. In this regard, hubs act as sources of information for new criminal ventures or sought-after partners due to their skills and personal traits. Accordingly, targeting well-connected offenders would be a possible means of disrupting a co-offending network in which popularity is a strong predictor of its evolution. Removing hubs from co-offending networks might help reduce crime by impacting the flow of information within the networks or removing key actors with unique traits. Implementing disruptive interventions seems suitable once LEAs have identified large connected components with many people - similar to those analysed in Chapter 6. Nevertheless, the mechanisms assessed in that Chapter also suggest that prior co-offending might predict future co-offences. This is especially relevant for co-offending networks in which reciprocity and reinforcement explain how their evolution, as these mechanisms rely on initial co-offences for future connections. Accordingly, an additional challenge is to disrupt incipient networks or unconnected groups that can merge and create complex structures similar to the components studied in Chapter 6.

Co-offending networks can also be disrupted by examining their members' crimes. If, for example, a particular network specialises in snatching mobile phones in the city centre, then crime prevention strategies should be tailored for this particular network operating in that particular area. The identification of co-offending groups and the assessment of their criminal specialisation, similar to the one presented in Chapter 7, can provide inputs for LEAs' definition of the problems they want to address to reduce crime (Goldstein, 1990). In this regard, the methodological approach through which the studies included in this thesis were conducted (i.e., the identification of co-offending networks and groups, the analysis of how they behave in time, and their tendency to specialised in certain crimes) can be used to identify recurring problems that are concerning members of the public and, subsequently, analyse the underlying causes, and set the goals intended to be achieved through crime-reduction interventions (Borrion et al., 2020; Clarke & Eck, 2005).

Disruptive interventions could also diminish the decision-making capacity (e.g., decisions about whom to select as an accomplice) and the flow of information (e.g., reducing the information about suitable crime-related opportunities). For example, posting crime-deterrent messages in venues open to the public, such as bars or pubs, can potentially modify how motivated offenders perceive and weigh the risks derived from co-offending. LEAs could also explore ways to tap into co-offending networks and insert information in the 'grapevine system' to diminish trust between potential accomplices. Similar interventions could also be considered for prisons that are the ultimate example of offender convergence settings, although some studies have shown that offenders do not create or expand their crime-conducive networks while incarcerated (e.g., Damm & Gorinas, 2020; Stevenson, 2017).

Unintended consequences derived from police-led interventions should be considered when disrupting co-offending networks. Research about the outcomes of these interventions is limited for co-offending networks, but a good starting point is to consider the findings in other sub-fields, especially in organised crime studies (e.g., Borrion et al., 2020; Diviák, van Nassau, Dijkstra, & Snijders, 2022; Morselli, Giguère, & Petit, 2007; Smith, 2021). Evidence suggests that *crackdowns* in which visible leaders are removed might explain variations in homicide rates. Violence increases as members fight to gain control over the organisation. Removing a leader could also increase violence as it might signal an opportunity for a rival group to attack the beheaded organisation (Braga, Weisburd, & Turchan, 2018; Felbab-Brown, 2013). For example, Calderón, Robles, Díaz-Cayeros, and Magaloni (2015) showed how the Mexican government's campaign launched in 2006 to counteract drug trafficking cartels by targeting kingpins increased cartels-related violence in the first six months after the intervention (e.g., inter and intra-group attacks) and the number of homicides targeting the general population (which lasted more than six months). This evidence can help co-offending researchers and LEAs frame questions to investigate plausible outcomes. However, it should not be interpreted as an argument to equate co-offending networks to organised crime groups. The questions that can arise by considering the findings produced elsewhere are: Would removing a hub in a co-offending network create a (violent) competition between other well-connected co-offenders? Do hubs in co-offending networks exert informal control over crime, territories or other co-offenders? What other strategic positions can be targeted in co-offending networks apart from the hubs? Regarding the latter, organised crime scholars have found that *brokers* play a vital role within illicit networks, as they bridge unconnected groups of nodes within a network (Newman, 2018) (see also the discussion about betweenness centrality in Chapter 3). For example, Morselli and Roy (2008) observed that nodes occupying these positions in an illicit network of exportation of stolen cars in Canada had a pivotal role since they introduced flexibility by bridging unconnected groups within the network. By connecting these groups, brokers allowed networks to remain resilient following police interventions. Although not directly tested here, the data presented in Chapter 6 suggests that some co-offenders might act as brokers. The reader will recall that the components analysed in that Chapter started as a set of unconnected cliques that merged into a large, sizeable component by the end of the study period (see Tables 6.2a - 6.2c). Testing the hypothesis that individuals act as brokers in co-offending networks is necessary. If such roles exist, some crime reduction can be expected by removing co-offenders who function as brokers, as they provide information about potential offenders and new opportunities for crime to unconnected groups. It is also possible that a lack of brokers could lead to a rise in the criminal specialisation as groups will be deprived of new opportunities, and offenders will be prevented from partnering with others who can assist them in committing new crimes when the two skill sets are combined.

Another unintended consequence is crime displacement. It refers to instances where interventions to reduce crime displace crime to other areas where crime-reduction programmes are not in place (Weisburd et al., 2006). However, displacement is not only geographical (i.e., criminal activities are shifted from one geographical area to another). It could also be temporal (criminal activities happen at different times or periods), in terms of the target (offenders focus on different targets or victims after the intervention), method (by changing their techniques or *modus operandi*), or offender (offenders or criminal groups relocate to continue their criminal activities) (Johnson, Guerette, & Bowers, 2014). Therefore, disruptive interventions targeting co-offending networks should consider crime displacement and attempt to measure it differently.

Like other police-led interventions, strategic and ethical considerations should be present when disrupting criminal networks. This thesis has shown an alternative to improve the understanding of the dynamics displayed by co-offending networks. This insight and tactical and policy-related concerns should help stakeholders decide on the intervention of particular co-offending groups. Moreover, practitioners would find the analytical strategy employed in Chapter 7 helpful as it illustrates how to identify meaningful substructures by mining official records. Identifying these substructures could help law enforcement agencies decide how to deploy their limited resources by, for example, gauging the number of co-offending groups operating in a city and determining which of these groups are causing harm to society (Sherman et al., 2016). Priorities could be set by enumerating such groups and understanding their behaviours (Berlusconi, 2017). The proposed analysis could be enriched by including geographical information to potentially reveal co-offending groups' hot spots and 'convergence settings' (Felson, 2003).

8.5 Positioning Bipartite Networks in Networked Criminology

When studying phenomena which involve connections between two types of entity (e.g., offenders and crimes), networked criminologists rarely study bipartite networks directly. They tend to project them into their one-mode versions due to the available tools to analyse this type of network. This thesis showed how the direct analysis of two-mode networks could offer substantial advantages when studying co-offending (see Chapters 5 and 7). The studies included here show, for example, how some network statistics can be biased when using one-mode projected networks and how bipartite networks can support the identification of meaningful substructures that resemble co-offending groups. These studies demonstrate why co-offending researchers should use co-offending networks' underlying, bipartite structure to avoid losing information and reporting biased statistics.

Networked criminology, in general, and co-offending studies, in particular, can benefit from bipartite networks. Furthermore, while the analysis here focused on links between individuals and crime events, several other relationships could be represented this way. For example, bipartite networks can encode the relationships between offenders and other crime-related entities (e.g., corporations, IP addresses, vehicles, victims, and bank accounts) (Xu & Chen, 2004). Incorporating various entities into co-offending studies can provide multiple perspectives of how offenders, for example, target victims and employ probes to execute crimes. Crime researchers and practitioners can also gain insights by identifying meaningful substructures within large bipartite networks through the algorithms designed for this purpose (e.g., Yen & Larremore, 2020). Examples of such substructures would include communities, generally defined as groups of nodes that connect to the rest of the network similarly. In a bipartite context, communities might represent groups of offenders involved in similar crimes or behaviours more generally. Similarly, /textit[bipartite motifs] can be used to identify relevant substructures in co-offending networks (Simmons et al., 2019). Motifs are the building blocks of large, complex networks observed more frequently than expected in a random network with the same number of nodes and edges (Milo et al., 2002). Extracting such substructures can give law enforcement agencies tactical advantages as these agencies continue to collect vast amounts of crime-related data, and bipartite networks are suitable to model the interactions between heterogeneous entities. Moreover, recently-developed algorithms can help LEAs and co-offending researchers identify missing connections in bipartite criminal networks. By showing possible connections, these algorithms can help address, in part, the ongoing problem of missing data in crime-related networks (for a review on these algorithms, see Alzahrani & Horadam, 2015).

Crime researchers and practitioners can also investigate missing links in co-offending bipartite networks (e.g. Isah, Neagu, & Trundle, 2015). These algorithms predict the likelihood of a link between two entities in a network (e.g., offender and criminal event) by using various similarity measures between entities. Employing link prediction algorithms in co-offending networks could help alleviate the limitations explained in Chapter 4 related to missing data by inferring links that are not visible but are likely to exist (Liben-Nowell & Kleinberg, 2003).

8.6 Future Work

This thesis faced a limitation in the absence of offender-level demographic information, as described in Chapter 4. Future research can then include this information to gain a more comprehensive understanding of co-offending networks' behaviours. For example, this data could be used to study assortative mixing in co-offending networks. Chapter 3 described this process as the tendency of nodes to create connections with similar others. Offenders' demographic information, accordingly, could be used to test a hypothesis about assortative mixing by age, sex, or criminal history. Such analysis, in turn, would help formulate the 'networked accomplice selection theory' mentioned above.

Future research could also include geographical information (e.g., place of residence and where offenders committed the crimes) to gain more insights into how adult co-offenders select their accomplices. Including such information would be helpful, especially when considering the mechanisms, such as triadic closure, with a geographical component as an underlying explanation (i.e., social foci/offenders' convergence settings). Practitioners will find this integration helpful as it would help them identify potential convergence centres of offenders. By intervening in such centres, some crime reduction might be expected; as contended by Tremblay (1993), some crimes depend on offenders' capability to find accomplices in these centres. As stated above, crime displacement can be unintended when disrupting a co-offending network. Hence, including geographical information could also provide insights into potential displacement following police-led interventions.

Co-offending networks capture a single relationship between offenders (i.e., who co-offended with whom), but this is an extreme simplification of the multiple types of ties between individuals. People are embedded in more complex social systems, and direct and indirect connections affect individuals' behaviours and decisions (Galaskiewicz & Wasserman, 1994). Accordingly, including the different interactions between offenders - and not only those derived from crime-related activities - could improve the analysis of co-offending in general and accomplice selection in particular. In particular, future research could examine co-offending networks through a *multilayer* approach. Multilayer networks consist of a fixed set of nodes connected by several different types of connection, represented by multiple layers (Newman, 2018), and have been studied across a wide range of contexts (Kivelä et al., 2014). However, investigating criminal networks through multilayer networks is rare and has primarily been limited to organised crime research (e.g. Ficara et al., 2021, 2022). In the present context, co-offending networks could be studied using a multilevel approach using different layers to represent specific crime types or time frames. Disaggregation by crime type has particular potential in this regard: this could be used to examine whether co-offending patterns differ across crime types or whether individuals tend to collaborate repeatedly on specific types of crime (i.e., specialise). Comparing and contrasting the layers in these networks can shed light on co-offenders' behaviours, which is an opportunity to refine this work. Practitioners might also find this approach promising. Network scientists have developed techniques to extract meaningful information from multiplex networks, such as communities of nodes that could correspond to co-offending groups (e.g., Pourhabibi, Ong, Kam, & Boo, 2021).

As mentioned in the introduction, Colombia faces several security challenges that made Bogotá an interesting setting to study co-offending. Attempting to explain co-offending patterns based on these challenges was beyond this thesis; however, future research could try to understand if these security challenges or other significant macro-social processes can explain variation in, for example, co-offending rates, co-offending participation rates (see Chapter 4) or the level of criminal specialisation in different locations (e.g., cities located in high-income countries v. those in middle and low-income countries). Likewise, another positive step to better understand co-offending is replicating the studies completed in this thesis to compare and contrast the results in other locations. As a field of study, co-offending needs more evidence from around the world to understand context-dependent variations that can help refine existing theories and new lines of inquiry.

These avenues for future research will allow co-offending to continue growing as a field of study. At the same time, it will help understand accomplice selection processes by producing valuable theoretical insights. Practitioners will also benefit from these research streams by incorporating these insights into the interventions aimed at disrupting co-offending networks and assessing their effectiveness and impact on individual and group behaviours.

Appendix A

Figures 8.1 and 8.2 present the observed clustering coefficients in one-mode and two-mode networks using windows of different size. Overlapping windows of size three provide a suitable number of data with a reasonable overlap between windows. The clustering coefficients vary slightly when increasing the number of years per window. For this reason, we completed our analysis using windows of size three.

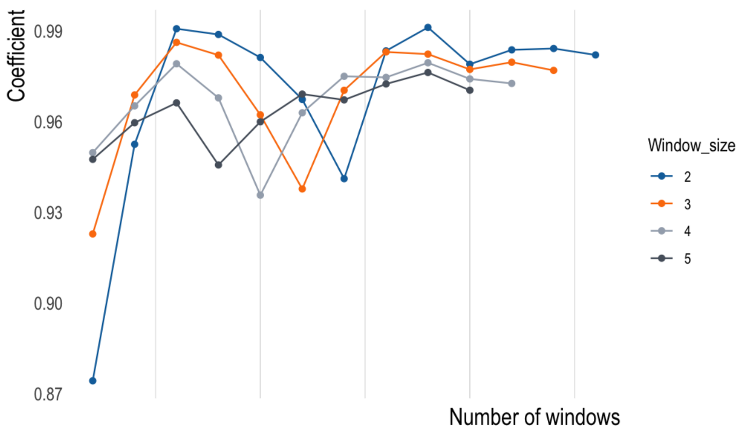


Figure 8.1: Observed clustering coefficients (y-axis) in one-mode networks between 2005 and 2018 (x-axis) using windows of different size. The first data point in x = 0 corresponds to the first window for each partitioning.

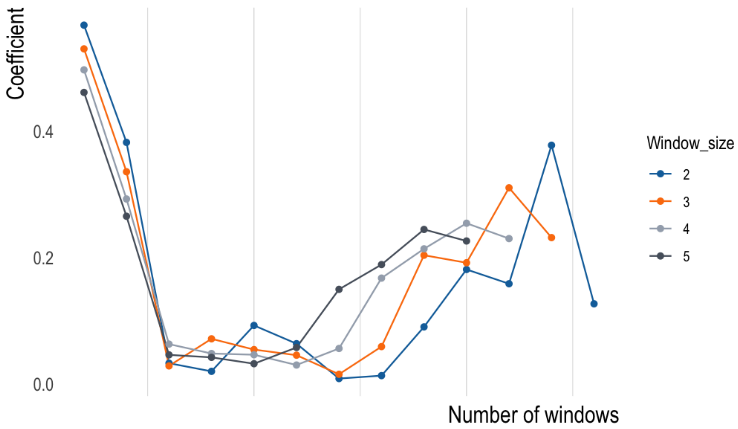


Figure 8.2: Observed clustering coefficients (y-axis) in two-mode networks between 2005 and 2018 (x-axis) using windows of different size. The first data point in x = 0 corresponds to the first window for each partitioning.

Appendix B

The regression coefficients can be biased when the proportion of 1's (i connection with j) to the 0's is small. In other words, when multiple potential accomplices exist, incoming co-offenders select a few. King and Zeng (2001) suggested using some control cases to prevent introducing a bias, such that any additional case included would not significantly increase the model's significance or decrease coefficients' standard errors.

We conducted two sensitivity analyses to determine the number of control cases: one for the network with 4.286 offenders and one for the other two. Both analyses used in-degree as a proxy of popularity. We used 5, 10, 20, 30, 40, and 60 control cases for the largest network and 2, 4, 6, 8, 10, 12, 14, 16, 18, and 20 for the one with 227 offenders. Since the analytical strategy implied using a simulated version of the original network, we simulated the network 100 times for each number of control cases.

The Wald χ^2 statistic allowed us to assess the significance of the models. Figure 8.3 presents the mean value of this statistic in each round of iterations and for each number of control cases. Figure 8.4 shows the mean value of standard errors for each independent variable (i.e., the four growth mechanisms considered). Considering how the Wald (χ^2) statistic and the standard errors behaved for each number of control cases, we considered that 30 control cases were an appropriate number to strike a balance suggested by King and Zeng (2001).

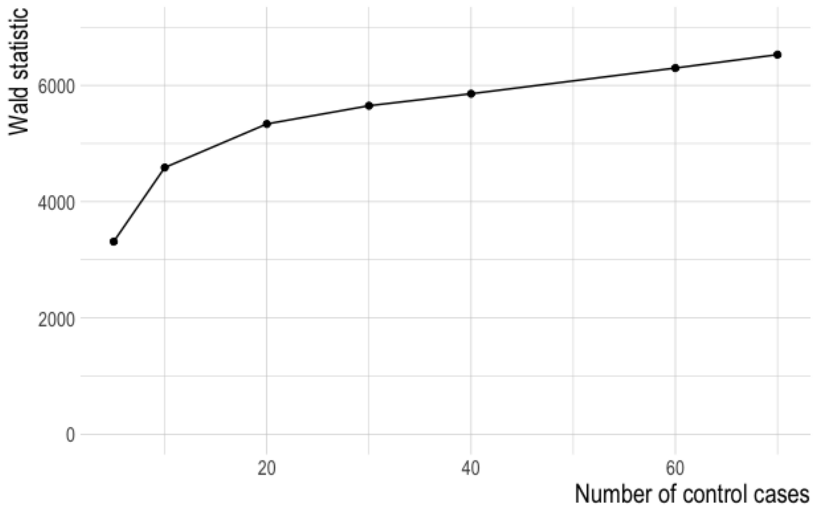
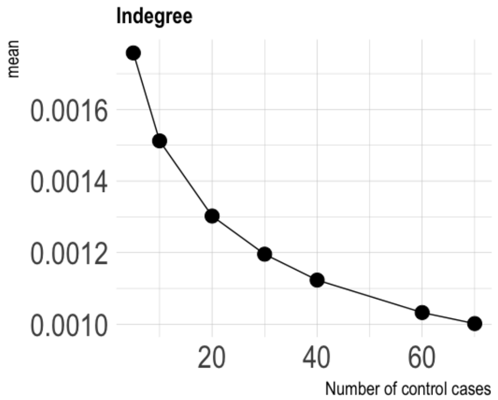
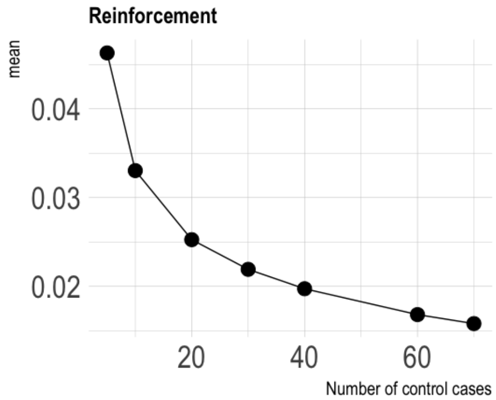


Figure 8.3: Mean value of the Wald statistic observed for each iteration using multiple number of control cases for the network with 4,286 nodes.

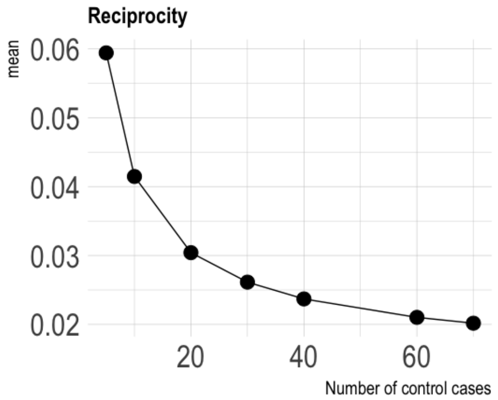
Figures 8.5 and 8.6 present similar figures for the network with 227 nodes. We agreed to use ten control cases for this network based on these results. Since the number of nodes is roughly similar, we also used the same number of control cases when analysing the network with 211 offenders.



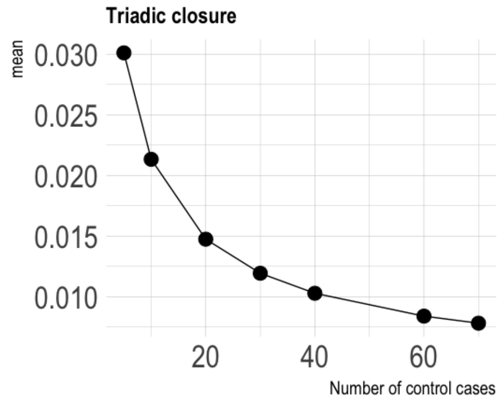
(a)



(b)



(c)



(d)

Figure 8.4: Mean value of standard errors yielded after 100 simulations for (a) indegree, (b) reinforcement, (c) reciprocity, and (d) triadic closure. Network: 4,286 nodes.

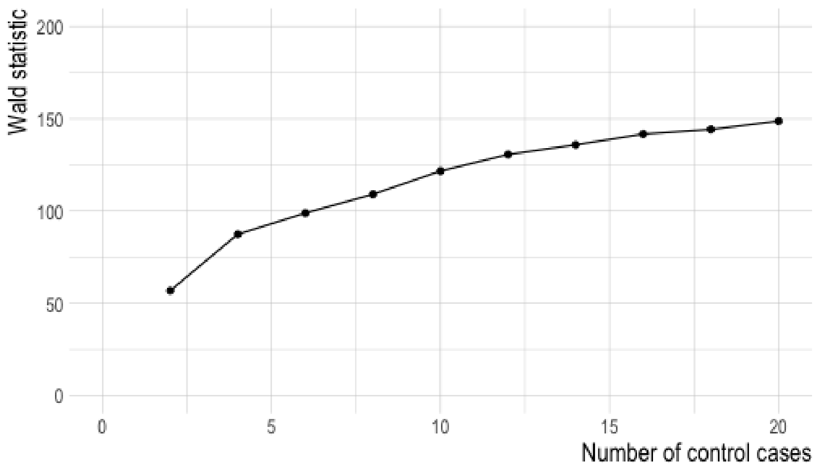
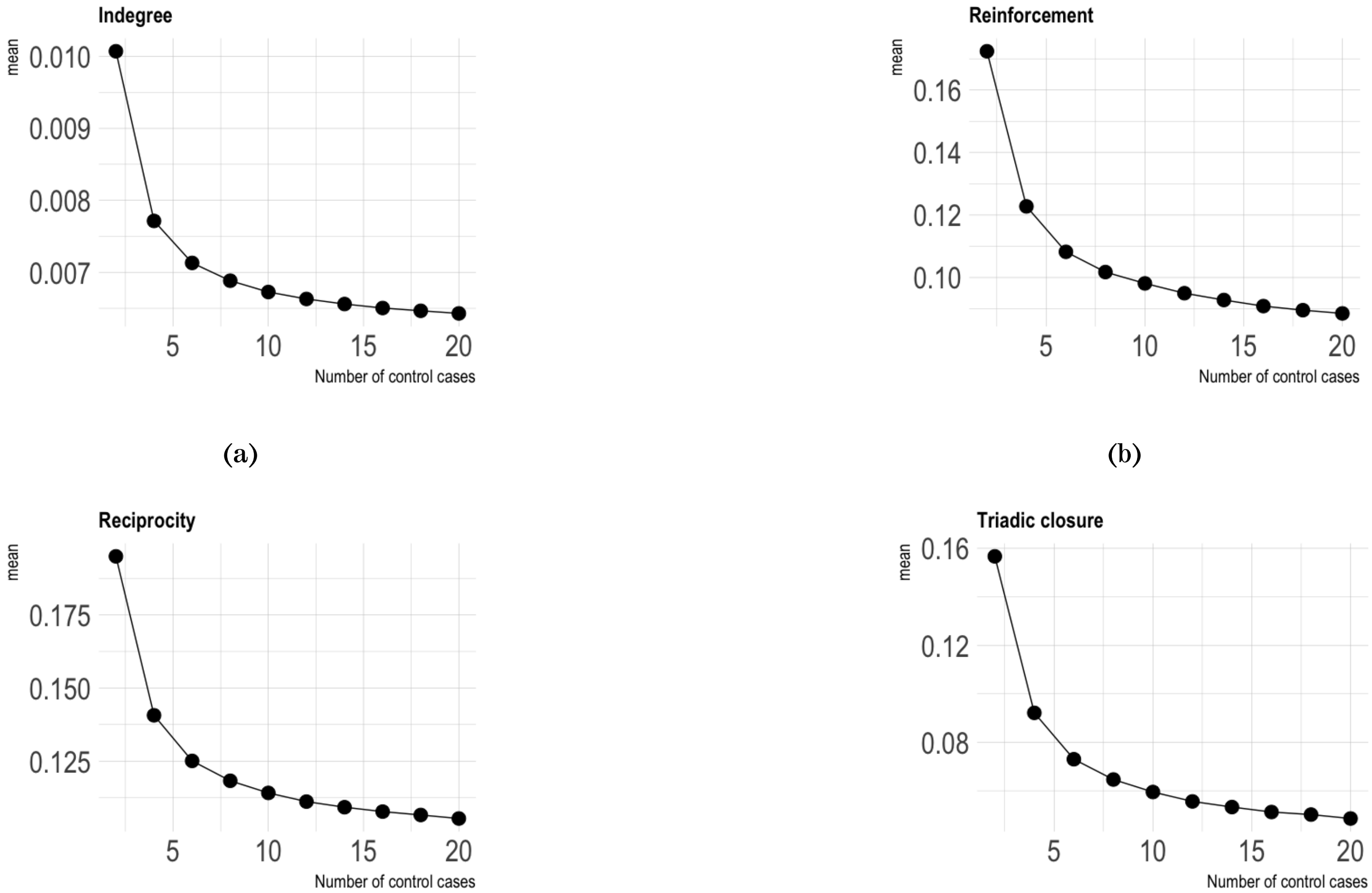


Figure 8.5: Mean value of the Wald statistic observed for each iteration using multiple number of control cases for the network with 270 nodes.

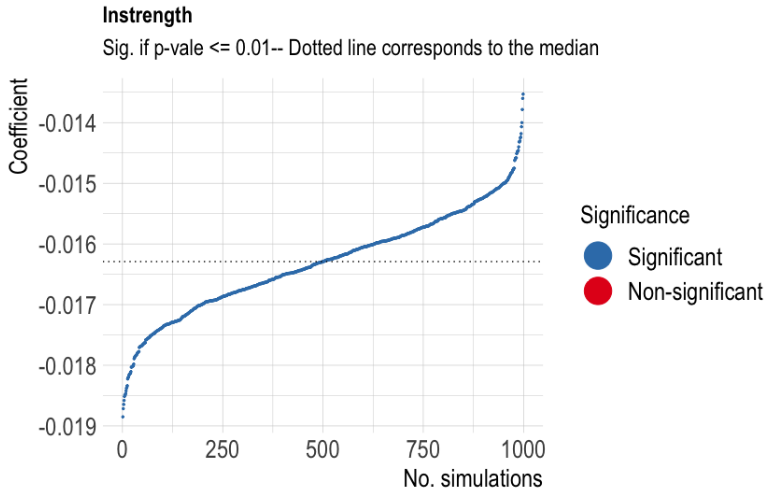


(a) (b) (c) (d)

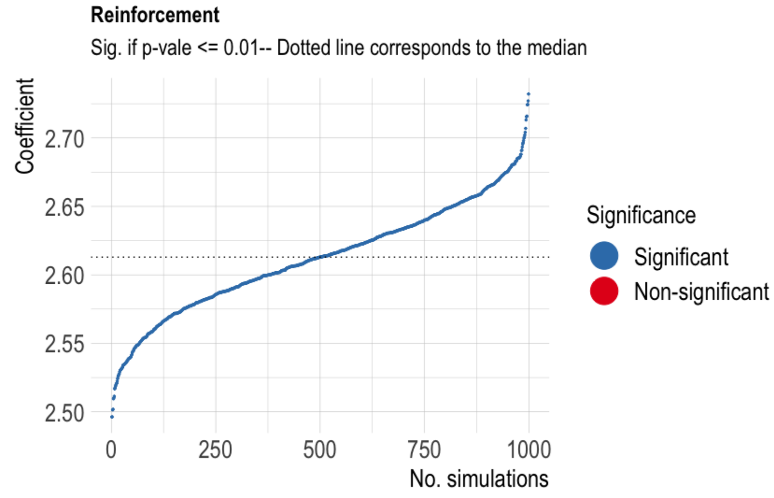
Figure 8.6: Mean value of standard errors yielded after 100 simulations for (a) indegree, (b) reinforcement, (c) reciprocity, and (d) triadic closure. Network: 270 nodes.

Appendix C

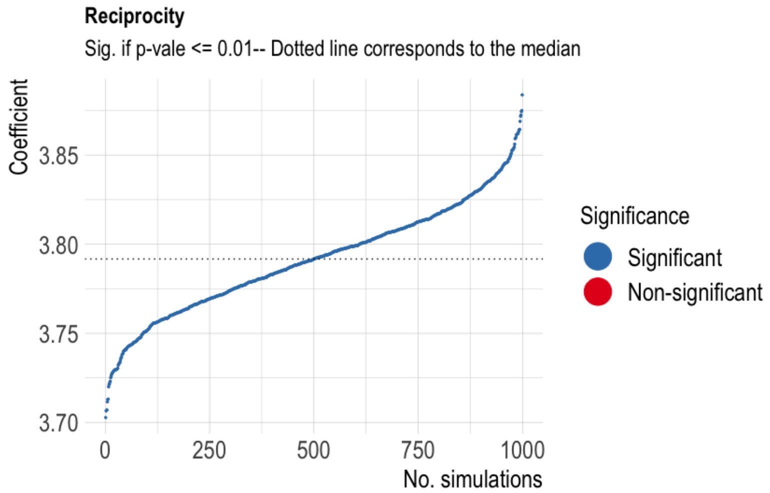
The following figures present the results of the simulations for three networks analysed here. Each network has two plots, one for each proxy of popularity (i.e., indegree, in-strength).



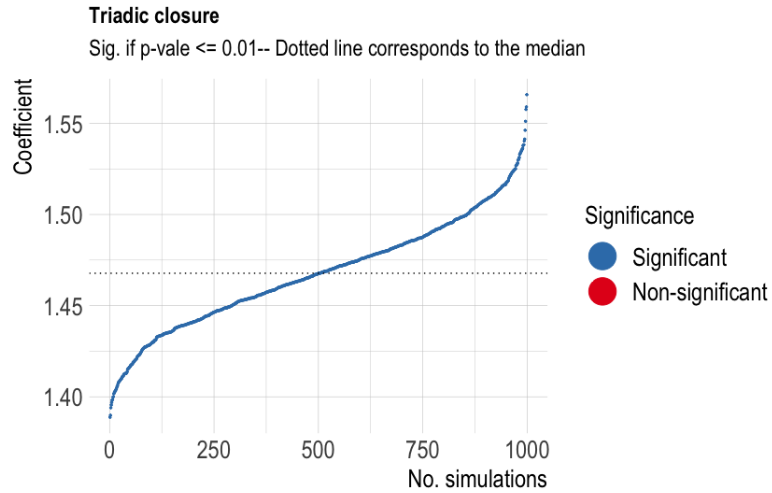
(a)



(b)

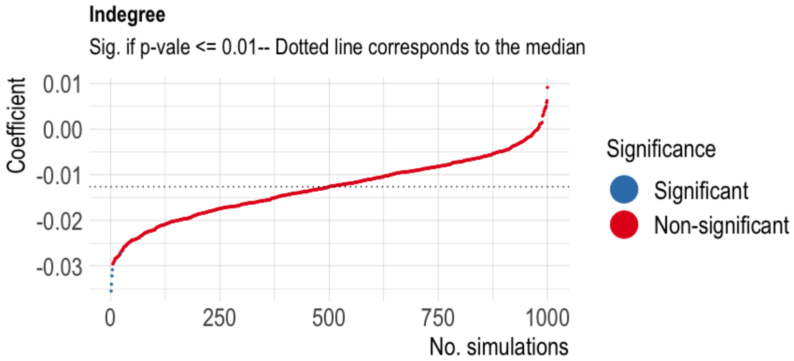


(c)

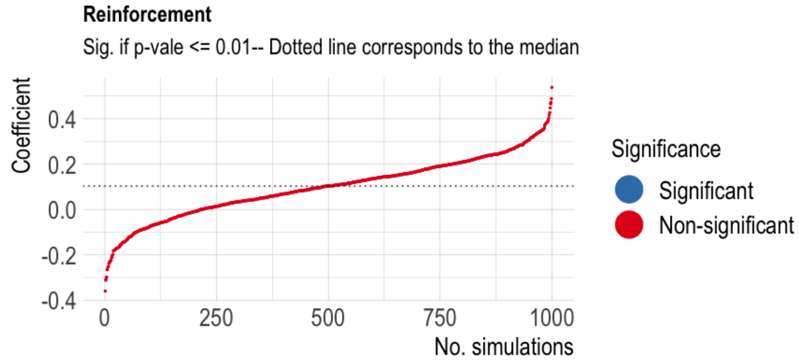


(d)

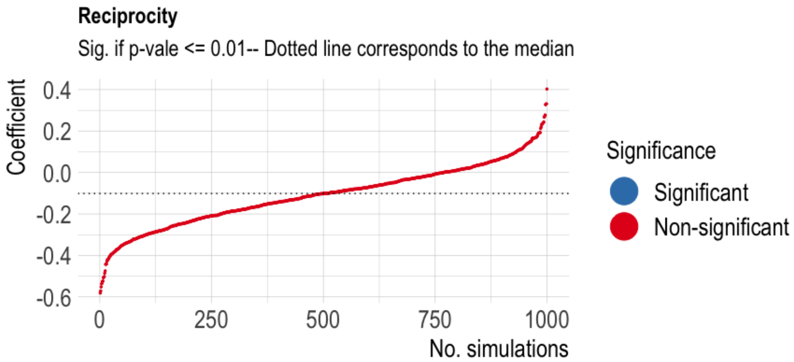
Figure 8.7: Results of the model for the network with 4,286 offenders jointly testing four growth mechanisms: (a) popularity (instrength as a proxy), (b) reinforcement, (c) reciprocity, and (d) triadic closure.



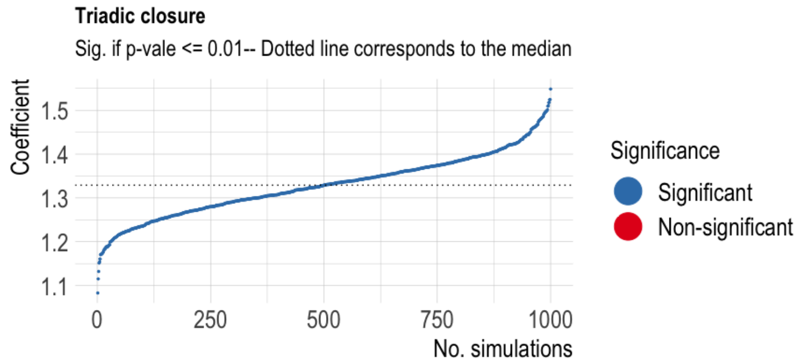
(a)



(b)

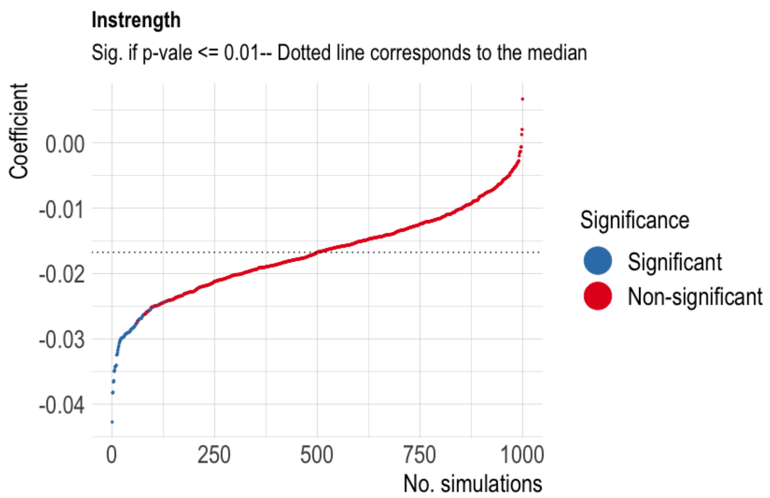


(c)

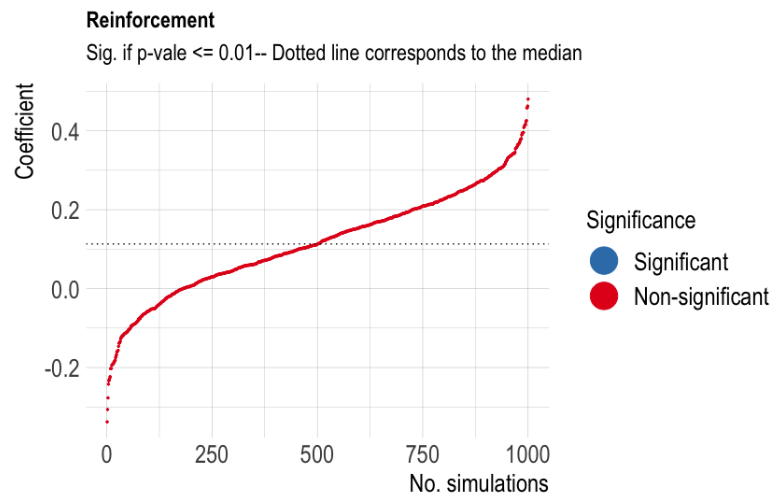


(d)

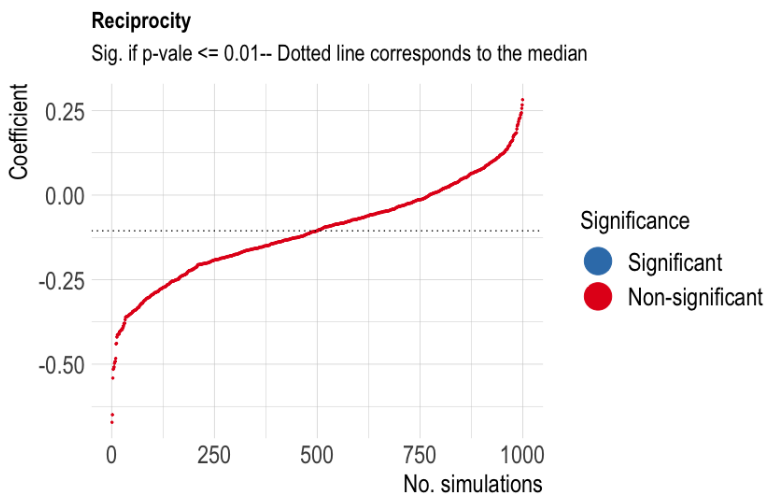
Figure 8.8: Results of the model for the network with 227 offenders jointly testing four growth mechanisms: (a) popularity (indegree as a proxy), (b) reinforcement, (c) reciprocity, and (d) triadic closure.



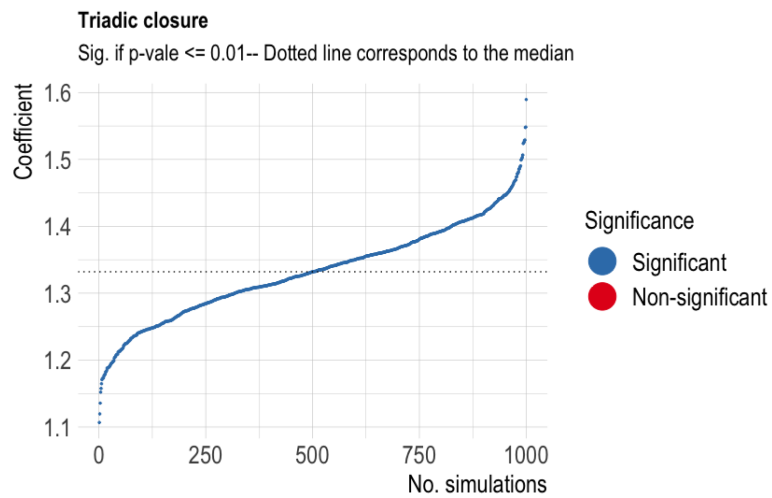
(a)



(b)

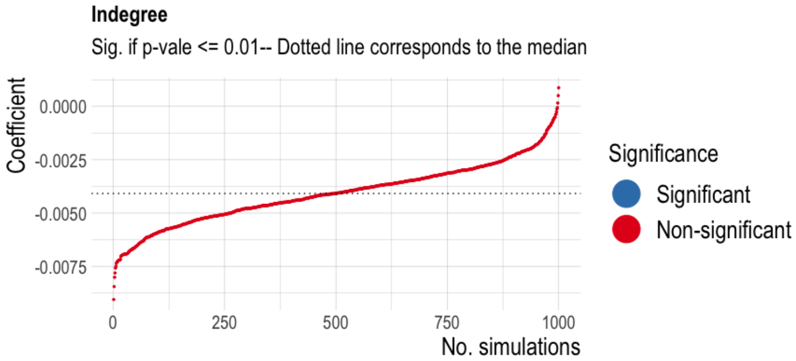


(c)

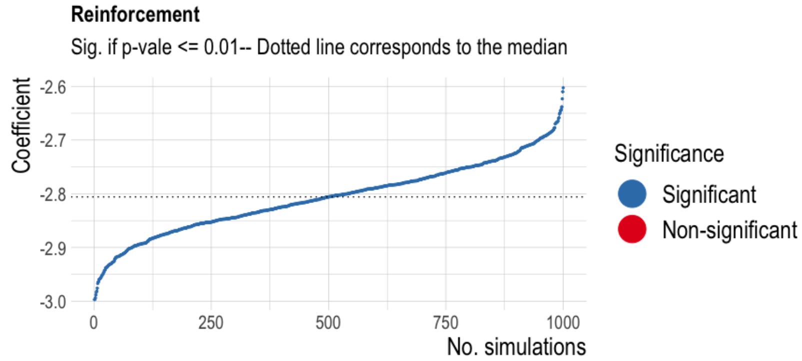


(d)

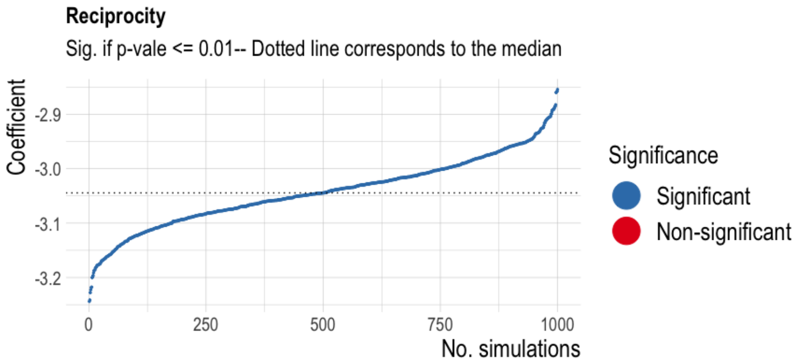
Figure 8.9: Results of the model for the network with 227 offenders jointly testing four growth mechanisms: (a) popularity (instrength as a proxy), (b) reinforcement, (c) reciprocity, and (d) triadic closure.



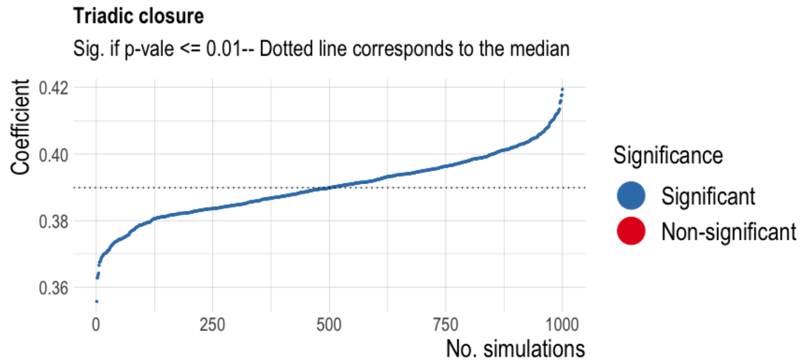
(a)



(b)

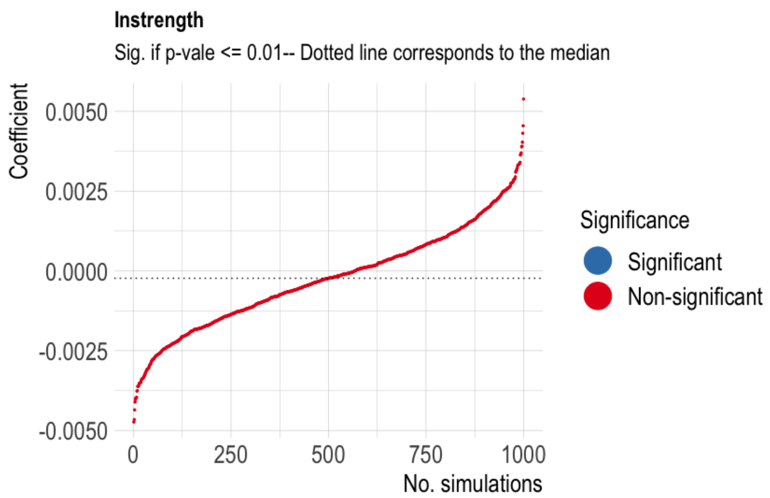


(c)

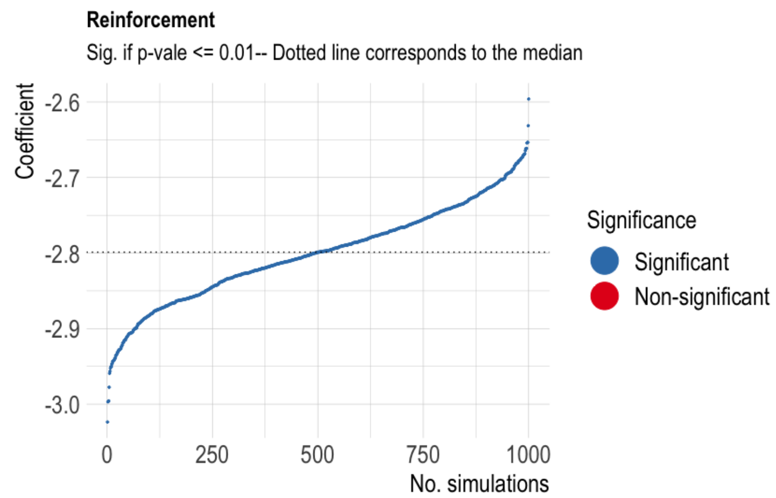


(d)

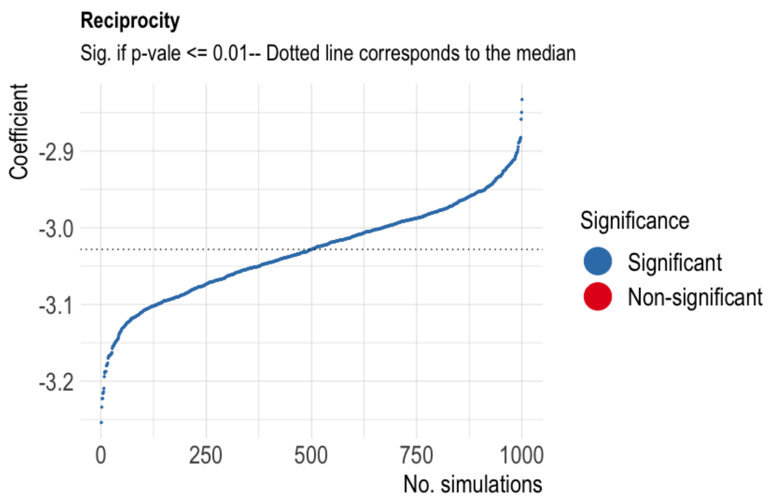
Figure 8.10: Results of the model for the network with 211 offenders jointly testing four growth mechanisms: (a) popularity (indegree as a proxy), (b) reinforcement, (c) reciprocity, and (d) triadic closure.



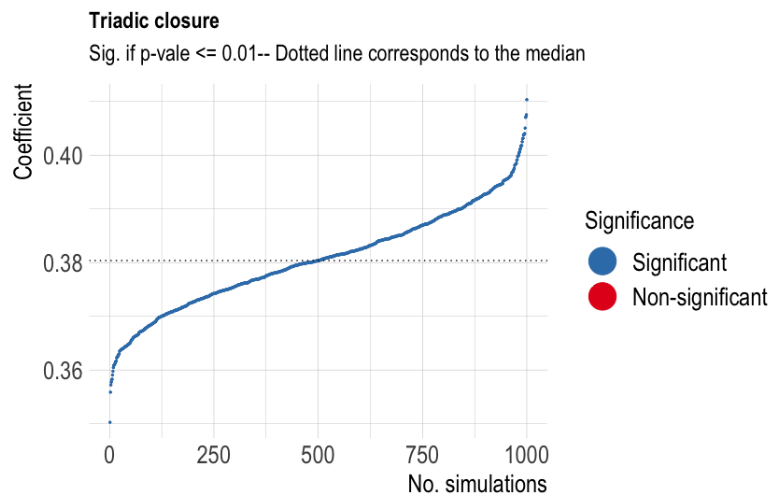
(a)



(b)



(c)



(d)

Figure 8.11: Results of the model for the network with 211 offenders jointly testing four growth mechanisms: (a) popularity (instrength as a proxy), (b) reinforcement, (c) reciprocity, and (d) triadic closure.

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