“Offending with the Accomplices of my Accomplices”: Evidence and Implications Regarding Triadic Closure in Co-offending Networks

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Abstract

We measured 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. We also assess the statistical significance of clustering coefficients using null models. The data relates to adult offenders (N = 274,689) connected to criminal investigations (N = 286,591) in Colombia. 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.

Key words: Triadic closure; co-offending networks; null models; bipartite networks

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Introduction

Just as it is in other walks of life, collaboration is a critical ingredient in criminality (Bouchard, 2020). 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 drug trafficking and other illicit 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 our 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 (for a review, see van Mastrigt, 2017). On one hand, such collaborations may simply 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. 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).

The analysis of networks linking offenders based on their co-participation in crimes can shed light on how individuals select their accomplices. One feature of co-offending networks that the literature has not thoroughly explored and that could explain how offenders find and select their accomplices is triadic closure — that is, 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. We should anticipate such a tendency if social networks mediate the accomplice selection, with the 'third' actor either providing the introduction or making assurances for trustworthiness.

Accordingly, this paper aims 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. Using records of criminal investigations relating to a wide range of crime types, we build co-offending networks and quantify the presence of triadic closure. Our 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.

We also contribute here 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 a high number of fully connected cliques, corresponding to instances where multiple actors have participated in the same crime. While these cliques contain many connected triads, many of these 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. In this work, we address this issue by adopting an approach developed by Opsahl (2013) which adjusts for the bipartite nature of the underlying data.

Background

While co-offending behaviour has been documented empirically in a range of studies, there has been comparatively little theoretical development concerning the mechanisms by which such collaborations come about (Weerman, 2014). Nevertheless, a number of general principles have been proposed as potential explanations for accomplice selection, across a range of contexts. In this section, we will outline these theoretical perspectives, and argue that they imply that co-offending networks are expected to exhibit some degree of triadic closure.

Accomplice Selection

The few theories that explain accomplice selection lay along a continuum (van Mastrigt, 2017). At one end, accomplice selection describes a spontaneous process arising from immediate circumstances. In this model, willing offenders are continuously signalling their readiness to offend to potential accomplices (Reiss, 1988; Alarid, Burton Jr, & Hochstetler, 2009); when a criminal opportunity then 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 are expected to maximise benefits and reduce costs (Tremblay, 1993; Weerman, 2003). In doing so, offenders evaluate potential partners based on their perceived trustworthiness (to minimise the risk of betrayal) and their ability to help maximise the expected rewards of the criminal venture (Tremblay, 1993). This evaluation involves judging accomplices' criminal capital — skills, information, and contacts deemed beneficial for the execution of a crime (Hochstetler, 2014).

A collective perspective of rationality can also explain the process of accomplice selection. For example, when faced with uncertain situations (e.g., living without a permanent shelter or starvation), individuals may recognise that personal needs can only be satisfied through activities that benefit others, including crimes. In this context, offenders are willing to cooperate with others in the execution of a crime to achieve this mutual benefit (McCarthy, Hagan, & Cohen, 1998), and so may choose accomplices who share their circumstances.

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 environment, both social and physical. 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, Aldridge, & Medina, 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 who are 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, Brantingham, & Andresen, 2017). Thus, individuals are more likely to co-offend with those who coincide in these same spaces simply because of the increased availability and potential for interaction.

As a typical example of this, 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 who are 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 previously, these judgements will take into account a range of 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 certain 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, and thus their reputations, built upon their behaviour in previous experiences, can also be considered part of their criminal capital.

Triadic closure in co-offending networks

The mechanisms outlined in the previous section imply that the formation of co-offending relationships is subject to a number of tendencies and dependencies. In turn, these will be expected to be manifested in co-offending networks in the form of structural regularities. While several such regularities might be anticipated, one in particular — *triadic closure* — arises consistently as a logical consequence of these mechanisms, and it is this property that will be the primary focus for our 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 are also friends (Holland & Leinhardt, 1971). Figure 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). Given that B and C share a common neighbour, triadic closure predicts that these two individuals are themselves likely to develop a direct connection (dashed line).

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, however, the mechanisms proposed 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, we expect 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

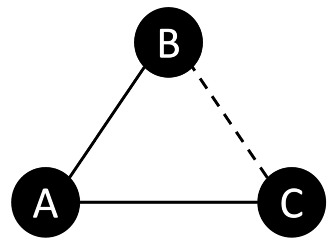


Figure 1: Example of triadic closure in social networks. The solid lines represent relationships between A-B and A-C. B and C are likely to be connected (dashed line) since they share a connection to a common individual, A.

(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 the individuals' reputations, all three have an incentive to observe social norms. Likewise, two actors can discipline a third for not complying with these norms (Wolff, 1950). The incentive for observing social norms, in turn, 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, mechanisms based on trust are expected to 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, etc.)' (p. 1016). Individuals who share a social focus, according to this theory, 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, therefore, 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, Smith-Lovin, & Cook, 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 the sharing of characteristics is itself transitive: if A is similar to both B and C, then B and C must be similar. Accordingly, any network which displays homophily is likely to exhibit some degree of triadic closure.

Co-offending relationships are likely to be 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, those in co-offending groups tend to be homogeneous in terms of their age, sex, ethnicity, or criminal experience (Weerman, 2003). Homophilic relationships may also arise as a consequence of 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, we expect to observe this trait 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, we should expect that this property will be observed in co-offending networks. Triadic closure is therefore our focus in this paper: we discuss how it can be measured accurately for co-offending networks, and examine whether it is present in a real-world network. In doing so, we do not seek to find support for any particular one of the mechanisms discussed above — or indeed to discriminate between them — but simply to establish whether this anticipated feature is present.

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 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 tends 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

$$c = \frac{t_\Delta}{t_<}, \tag{1}$$

where t_Δ is the number of closed triads and $t_<$ is the total number of (open and closed) triads. A coefficient near to 1 suggests that relationships are transitive (i.e., accomplices of an offender are also accomplices). One near to 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 we construct co-offending networks based on the joint-participation in criminal events, an implicit first step is creating a bipartite (or two-mode) network representing links between offenders and crimes. Figure 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, we can derive a co-offending network 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 2(b) is the one-mode projection associated with the example introduced above. We can then examine the resulting one-mode network using standard metrics and measures like the clustering coefficient.

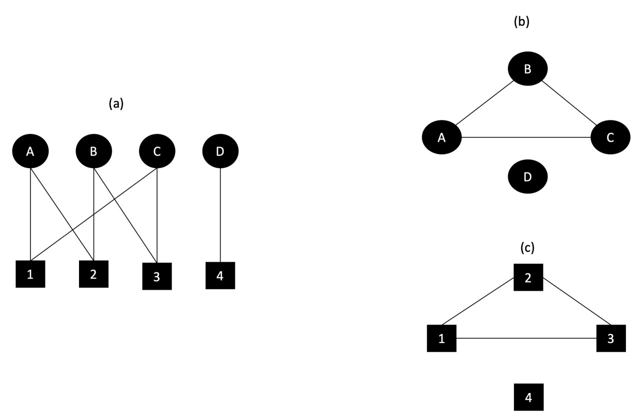


Figure 2: (a) Bipartite network with four nodes per mode and its two, one-mode projections (b and c). Nodes connected to a common node in the original bipartite network will be connected in the one-mode projection.

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, we can consider one-mode projections as the union of multiple cliques (Newman, 2018), with each one 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, we expect 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 is the result of 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 3). When we calculate standard clustering coefficients for one-mode projections, this issue means that they have the potential to substantially over-estimate the level of triadic closure since many of the closed triangles identified may be due to single crimes.

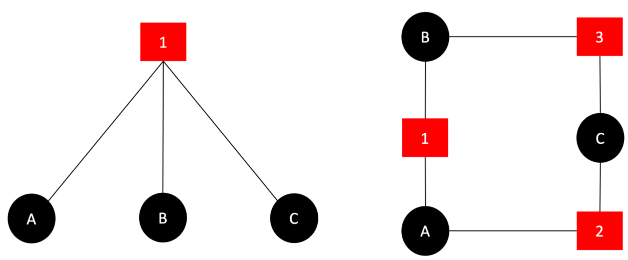


Figure 3: Two configurations of bipartite, co-offending networks:(a) three offenders (A-C) connected to a single investigation (1), and (b) three offenders (A-C) linked to three different investigations (1-3). Both components yield a closed triangle in the one-mode projection of offenders (A-C).

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. Consequently, 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 back 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. 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 3 (a) is one such example). Thus, by reframing the calculation in terms of 4-paths in the original bipartite networks, we can 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 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 4(b)).[2] Note, however, that the one-mode projection has three additional paths of length two — between nodes B, C, and D — since they are connected to the same event, '3'. By 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

$$C_{bn} = \frac{\rho_c}{\rho}, \tag{2}$$

where ρ_c is the number of closed paths of length 4, and ρ is the total number of paths of length

[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)

4, both open and closed. Since, as mentioned above, these 4-paths correspond to triads in the one-mode projection, the coefficient, therefore, measures the proportion of such triads that are closed — while, crucially, omitting those created by three or more offenders linked to the same criminal event.

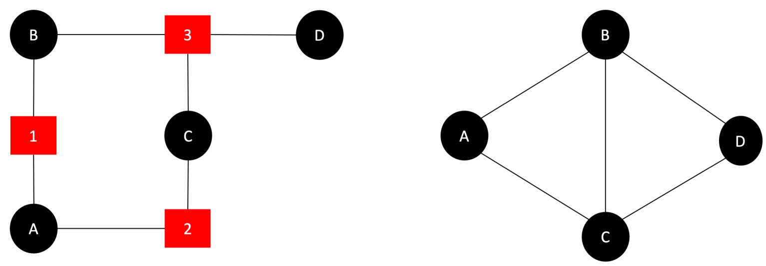


Figure 4: (a) Bipartite networks with four offenders (A-D) and three investigations (1-3). (b) One-mode projection of the bipartite network. One-mode projection has additional paths of length two.

As well as the coefficient itself, Opsahl (2013) also shows how the calculated values can be compared to those that would be 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.

The following section presents the data we used to assess transitivity in co-offending networks, modelling the interaction between offenders and criminal events.

Data, analytical strategy, and results

We used data retrieved from the Colombian Attorney General's Office (AGO), the authority in charge of investigating and prosecuting offenders before courts of Law. The data set contained information about criminal investigations in Bogotá between 01/01/2005 and 31/12/2018 related to all seventeen categories of crimes included in the Criminal Code. To better understand the population of co-offenders in this city, we included information about investigations that were either on trial (as of December 2019) or had a guilty verdict or guilty plea. The observations also included those cases that exceeded the time granted by the Criminal Procedural Law to reach a final decision and had therefore been closed by the AGO as required.[3]

Each observation in the data set consisted of a single offender related to a specific criminal investigation. Therefore, we used the (encrypted) national identity number (NIN) to identify each offender and the Criminal Investigation Record Number (CIRN) to identify individual criminal investigations.

We partitioned the data into twelve rolling-temporal windows of three years duration (2005-2007; 2006-2008; (...) ; 2016-2018). This window size provides a suitable number of data points (i.e., windows) with a reasonable overlap between windows. The sensitivity analysis in the Appendix also shows that the results only vary slightly with the value of this parameter.

Then, using the R package *igraph* (Csardi & Nepusz, 2006), we created a bipartite network for each window. Table 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 1: Number of offenders, co-offenders, investigations, investigations related to co-offenders, and components per window in Bogotá (2005-2018).

Window	Offenders	Co-offenders	Investigations	Multi-person investigations	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

We calculated the clustering coefficients of these bipartite networks, as per the approach

[3]Some defendants try to prolong the length of trials to exceed the limit granted by the Law. Once trials exceed this limit, the judges must declare an investigation closed, avoiding reaching a final decision. Due to the prevalence of this malpractice, this study included this type of case.

described in the previous section, using the R package *tnet* (Opsahl, 2009). Table 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 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.

Table 2: Bipartite clustering coefficients, closed paths of length four, total paths of length four, and corresponding one-mode clustering coefficients

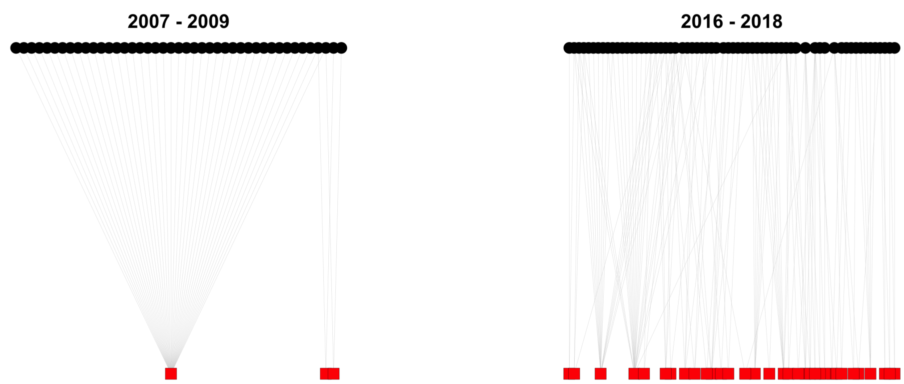
Window	Bipartite clutering coefficient (C_{bn})	Closed paths of length 4	Paths of length 4	One-mode clustering coefficient (C)
1	0.53	102,468	193,134	0.92
2	0.34	32,708	97,378	0.97
3	0.03	972	34,244	0.99
4	0.07	2,734	38,350	0.98
5	0.05	2,622	48,344	0.96
6	0.05	2,360	52,018	0.94
7	0.02	1,264	83,388	0.97
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

A number of patterns can be 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 sense. In real terms, C_{bn} corresponds to the probability that 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%.

It is also notable that the values of C_{bn} fluctuate considerably across windows. The coefficient reaches its highest value, 0.53, in 2005-2007 (Window 1), before dropping to 0.03 a couple of years later. It then remains low until 2011-2013 (Window 7), before rising again in later windows; by the final window, it reaches 0.23. Temporal fluctuations in clustering coefficients have been reported elsewhere (e.g., Amblard, Casteigts, Flocchini, Quattrociocchi, & Santoro, 2011) for other forms of network (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.

To find a possible explanation for these fluctuations, it is worth examining the relationship between C_{bn} and other network features. 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.

Even more notable, however, is the pronounced fluctuation in the number of paths of length 4 in the networks, which also mirrors that of C_{bn}. In real-world terms, each 4-path corresponds to an instance where an offender has co-offended with 2 others, via 2 distinct offences, and so there is clearly wide variation in the prevalence of such cases. Some insight into this can be gained by examining the networks graphically: in Figure 5, we plot the largest connected component for two contrasting windows, in bipartite form. Comparing these two diagrams, it can be seen that the participants in distinct events overlap to a much greater extent in Window 12, in which 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.



(a) Window 3 (b) Window 12

Figure 5: Bipartite plots of largest connected components: a) Window 3, which contains 43 offenders and 3 events, and has 160 paths of length 4; and b) 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 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 together — can quickly generate large numbers of 4-paths. This can also be expressed in terms of components: as more components merge with each other (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 that 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, to our knowledge, is the first one 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 fact that our dataset contains 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; we argue 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, we are not yet in a position to say whether they nevertheless represent significant levels of triadic closure. However, as explained in the previous section, we can 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 have no tendency to co-offend together, this coefficient should be equal to 0 in the null model.

The null model we used here consisted of 1,000 randomised simulations of each of the twelve bipartite networks. Each simulation consisted of 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, we calculated the clustering coefficient using Opsahl's approach.

Table 3 presents the observed coefficients alongside the 97.5 percentile of the null model. In all cases, the 97.5 percentile values are exceptionally small ($<$0.001), likely reflecting the sparse nature of the underlying networks. Consequently, the observed values are 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 our 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 per cent 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 would be expected without a triadic closure effect.

Table 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

Discussion and conclusion

This paper 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 a number of theories relating to criminal accomplice selection, which is the mechanism which drives link formation in such networks. In our analysis, we sought to verify that triadic closure was indeed present in a co-offending network from Bogotá, Colombia, and to measure its extent in a rigorous way. In doing so, we more broadly addressed Bichler's (2019) *theory of networked opportunity* by examining the influence of social networks on the decisions of offenders.

As far as we are aware, this article is the first to measure triadic closure in a set of relatively large networks of co-offenders using the original bipartite version of these networks. Unlike previous studies, we used data that 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, UK, and the USA). Moreover, we also used a null model to assess the significance of the clustering coefficients. Although this technique is widely used in other disciplines employing SNA (e.g., ecology), networked criminologists have not typically employed this approach to assess the statistical significance of network statistics or test hypotheses.

In our network, the probability of observing a co-offending relationship between the accomplices of an offender ranged from 3 to 53 per cent. 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.

Our findings are consistent with a number of theories relating to accomplice selection, encompassing mechanisms such as trust, geographical proximity and homophily. We do not make any attempt here to distinguish between these mechanisms, and indeed to do so would not be possible with the available data. However, having verified that triadic closure is present as predicted, we will address this question in future work once detailed information about criminal events (e.g., where they occurred) and offenders (e.g., demographic characteristics and previous interactions with the criminal system) becomes available.

In the last three decades, security and crime researchers have illuminated dark, covert networks using social network analysis. Some reports show that dark networks have distinctive features, setting them apart from 'bright' networks (see, for example, Morselli, Giguère, & Petit, 2007). However, our findings suggest that dark networks — the example studied here concerned criminal behaviour — may share some characteristics with 'bright', legitimate networks, and therefore that findings in this domain may be interpreted more broadly. Here, transitive relationships were expected due to the overlap between accomplice selection theories and those explaining triadic closure. Given the broad applicability of theories relating to transitivity in network science as a whole, the results add weight to the growing evidence base that clustering may be a universal property of social networks.

One interesting feature of our 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 we cannot be sure of 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. Clearly, observing triadic closure is dependent on law enforcement agencies' ability in detecting crime and revealing connections between known offenders. Assessing the historical capacity of Colombia's Prosecution Office and its impact on triadic closure in co-offending networks is beyond the scope of this article. 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 we included time in the analysis of co-offending networks, we did not consider the order in which offenders executed crimes: 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, our results highlight the importance of accounting for the bipartite nature of co-offending data when performing analysis. We demonstrated that the typical approach of taking the one-mode projection and calculating standard clustering coefficients results in extremely (perhaps implausibly) high 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 discrepancy in values suggests that the modified approach proposed by Opsahl (2013) generates accurate values.

Despite the novel features included here, this study faces several limitations. Co-offending, as 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,[4]

[4]Prosecutors need to have some level of certainty about offenders' responsibility before starting the trial.

a court of Law could acquit some of the individuals included in the data set. This possibility means that the data may contain information about people who were not ultimately convicted. We also decided to remove 12.7 per cent (51668) of the observations since they yielded an error during the encryption process of the NINs. The AGO used the MD5 algorithm to encrypt these numbers, and it returned errors for missing values and NINs that included special characters or blank spaces. Without the original numbers, it was not possible to run a node disambiguation process (Newman, 2018) to know the exact number of unique individuals represented in the observations that yielded an error; hence, we excluded them from the analysis.

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, we need 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.

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Appendix

Figures 6 and 7 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 only vary slightly when increasing the number of years per window. For this reason, we completed our analysis using windows of size three.

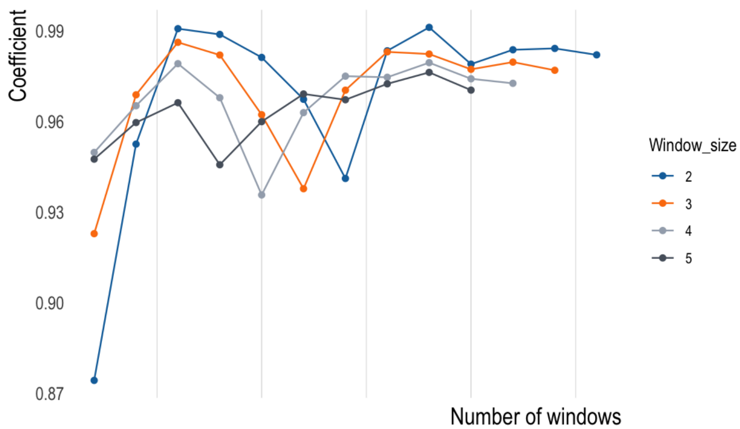

Figure 6: Observed clustering coefficients (y-axis) in one-mode networks between 2005 and 2018 (x-axis) using windows of different size. The first data point in x = 0 corresponds to the first window for each partitioning.

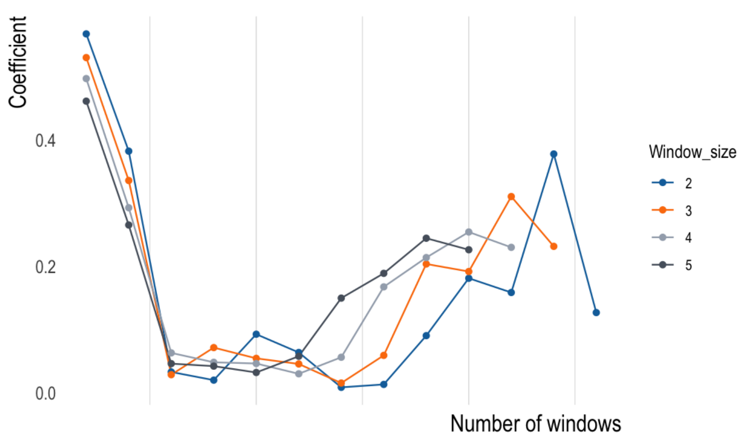

Figure 7: Observed clustering coefficients (y-axis) in two-mode networks between 2005 and 2018 (x-axis) using windows of different size. The first data point in x = 0 corresponds to the first window for each partitioning.

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