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Exploring criminal specialisation in co-offending groups

Alberto Nieto[a], Toby Davies[b] and Hervé Borrion[a]

[a]Department of Security and Crime Science, University College London (UCL), London, UK; [b]School of Law, University of Leeds, Leeds, UK

ABSTRACT

Researchers have studied criminal specialisation at the offenders' level to understand criminal careers. Despite criminal careers comprising events in which offenders co-offend with others, we know less about the extent of co-offending groups showing signs of becoming specialists. To start addressing this gap, in this study we report a method through which we identified 1,796 co-offending groups in a network containing information about adult offenders ($n = 76{,}697$) connected to criminal investigations ($m = 35{,}604$) between 2010 and 2018. During this timeframe, 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. These results suggest that criminal specialisation is a characteristic also shared by co-offending groups. Criminologists and practitioners might find helpful the method employed here to identify co-offending groups and assess their level of specialisation.

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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, rather, specialise in particular crimes (e.g. Blumstein, Cohen, Das, et al., 1988; Britt, 1996; Farrington et al., 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 et al., 2005; McGloin et al., 2007; Shover, 2018; Steffensmeier & Ulmer, 2017; Sullivan et al., 2006). 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, 1988; Reiss &

CONTACT Alberto Nieto uctznie@ucl.ac.uk Department of Security and Crime Science, University College London (UCL), 35 Tavistock Square, London WC1H 9EZ, UK

Farrington, 1991; Tremblay, 1993). The limited research on the criminal specialisation of co-offending groups suggests that juvenile groups specialise in some crimes (e.g. McGloin & Piquero, 2010; Warr, 1996). 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 useful to refine or falsify them (Sullivan et al., 2006). As an example, Mazerolle et al. (2000) suggest that differential opportunity theory (Cloward & Ohlin, 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's (1990) theory posits that illegal activities are committed by individuals who lack self-control. Due to the lack of self-control, individuals would favour any opportunities that are easy to seize and deliver immediate gratification (i.e. low-hanging fruits), making them prone to become 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 in order to design interventions aimed at preventing criminal activity (Blumstein & Blumstein, 1986). 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) 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 so 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 common (Guerette & Bowers, 2009). Accordingly, understanding the criminal specialisation of co-offenders – coupled with tools, such as crime scripts (Cornish & Clarke, 2002), that help understand how crimes are executed – can assist law

enforcement agencies in deciding how to allocate the limited resources they have (Morselli, 2009).

We explored criminal specialisation among adult co-offenders using a dataset containing information about criminal investigations in Bogota (Colombia) between 2010 and 2018. We identified co-offending groups in a network representing the relationships between offenders ($n = 76{,}697$) and criminal investigations ($m = 35{,}604$) 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 (Grund & Morselli, 2017; Mazerolle et al., 2000; McGloin et al., 2007; Piquero et al., 1999).

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 investigations).

Co-offending groups and criminal specialisation

Most evidence concerning co-offending groups comes from Australia, Canada, the Netherlands, Sweden, the UK, and the U.S.A. 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 do differ across age groups and settings. Juvenile offenders, for example, co-offend most often (Lantz & Ruback, 2017), but tend 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 prior to 2011 and found that those in Canada and England exhibited a similar pattern, while those in the U.S.A. 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 U.S.A. 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 U.S.A. had four or more members. While this might indicate that co-offending groups are more prominent in the U.S.A., the time frame of the studies (Canada, 1992–1999; England, 2002–2005; and the

U.S.A., 2008) and data sources (criminal incidents recorded by the police in Canada and England, and victimisation reports in the U.S.A.) could explain the differences.

The tendency for co-offending groups to be small also applies when the groups in question are part of larger organisations. Bright et al. (2022), for example, found that members of outlaw motorcycle gangs tended to offend together in small groups, across a range of crime types. 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 (Carrington, 2002; Lantz & Ruback, 2017; Reiss, 1988; Warr, 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; S. B. van Mastrigt, 2017; Warr, 1996, 2002; Weerman, 2003, 2014). Continued offending with the same accomplices appears to be the exception, although larger groups with more varied offending patterns have been shown to persist over the longest periods (Lantz & Hutchison, 2015). 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, 1988; Reiss & Farrington, 1991; Tremblay, 1993). Additionally, residential mobility, incapacitation through arrest or incarceration, and shifts to conventional careers may explain why some individuals stop co-offending altogether, temporarily, 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 U.S.A., 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) studied a sample of juvenile offenders identified in Philadelphia in 1987, and examined whether their criminal specialisation was associated with the structure of their co-offending networks[1]. In particular, the study was concerned with the concept of *network redundancy*. An individual's network of co-offenders is said to be redundant if their associates tend to be linked to each other – this is related to structural equivalence, since associates that are structurally equivalent will tend to have redundant edges between each other. In this work, it was hypothesised that non-redundant networks will be conducive to criminal versatility, since the lack of overlap means that individuals will be exposed to diverse knowledge and opportunities. Redundant networks, on the other hand, may be homogeneous and insular, decreasing the chance of learning about new criminal opportunities (Wasserman & Faust, 1994). According to McGloin and Piquero's (2010) findings, juvenile offenders who belong to less redundant networks tend to commit different types of crimes, whereas those who belong to more redundant networks tend to specialise. The authors 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.

More recently, Bright et al. (2024) examined data from Australia in order to investigate the versatility of offending within co-offending groups. Although the results do not relate to specialisation in the same sense as studied elsewhere they examine whether individual events are likely to involve multiple crime types – their results still shed light on the extent to which groups exhibit diverse behaviours. Their findings indicate that crime events involving co-offending groups are more likely to feature multiple crime types than those involving solo offenders. Furthermore, they show that versatility evolves as groups mature, and that – consistent with Grund and Morselli (2017) - the prior experience of group members influences the types of crime that will be committed when offending together.

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 produced so far 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.

Method

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

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, we used as our starting point the definition provided by Warr (1996), which states that whenever two or more individuals come together to execute a crime, they constitute a co-offending group. We then expanded the scope of this definition 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 our definition, therefore, we do not have any requirements about the internal dynamics of a group: involvement in the execution of a crime is all that is required.

Previous field studies in criminology have focused on particular types of criminal group. These groups can be distinguished by their members' age (e.g. juvenile gangs), the interests shared by their affiliates (e.g. outlaw motorcycle gangs), the crimes in which they participate (e.g. transnational drug cartels or human trafficking networks), or the locations in which they tend to spend their time or commit crimes (e.g. street gangs). These classifications are useful as they draw boundaries that allow researchers to focus on specific collectivities linked to criminal activities; furthermore, several of these groups have distinctive organisational structures and dynamics that are of interest in their own right. In our study, however, we are concerned specifically with co-offending, and so define groups explicitly with respect to this, rather than in a sociological or functional sense. While other criminal organisations may work collectively towards a broad function, this does not always equate to co-participation in crime: not all group members co-execute the same crimes together, and members can co-offend with people outside their groups. Moreover, accessing information about group affiliation can be challenging,

especially if these groups want to remain undetectable. Hence, we use the proposed definition for this study as it considers collaborations between offenders regardless of their (imposed or self-declared) affiliations.

According to the proposed 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 investigations and their participants. These records are, of course, subject to known limitations (Campana & Varese, 2020). 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, and this is, to some extent, dependent on law enforcement agencies' allocation of resources to each investigation. Notwithstanding these limitations, official 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. 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.[1]

Data

We identified the participants of criminal investigations using information held by Colombia's Attorney General's Office (AGO).[2] These investigations are typically initiated through victims' reports or police-led initiatives. The AGO analyses the information contained in the reports and, if there is sufficient merit, will open an inquiry to compile the required evidence about the crime(s) and those involved. Once a particular person is identified as a potential offender during this initial stage, the AGO will notify this person that they have been linked to a criminal inquiry and that they are under investigation (*imputación*). If offenders are arrested red-handed, they will also be linked to an investigation, and the AGO will serve this same notification once a judge has decided about the legality of the process undertaken by the police before, during, and after an individual has been arrested. Note that not all investigations will necessarily involve an arrest, but all arrests will be associated with an investigation. In either scenario, the AGO must have a minimal level of certainty about the connection between the criminal event and the individual under investigation before serving these notifications.

We used data on all closed and ongoing criminal investigations involving adult offenders in Colombia's capital, Bogota, between 1 January 2010 and 31 December 2018. We considered only investigations that were processed under Law 906/2004, which only applies to adult offenders (i.e. those aged 18 or above); minors are processed under different regulations, even if they committed a crime with an adult. By *ongoing criminal investigation*, we refer to those investigations in which the AGO has notified a defendant that they are under investigation, not to those initial inquiries completed based on victims' reports. In our analysis, we consider only investigations which feature two or more offenders: there are 35,604 such investigations, featuring 76,697 unique co-offenders.

The AGO identifies criminal investigations through a unique code, and individual offenders are referred to by their (encrypted) national identity numbers. Each record in

our 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 our dataset, and each observation would share the investigation's identifier code. Each record also contains the offender's classification under Colombian Criminal Law as either an *author* or a *participant*. 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. accessories or those who encouraged the crime without participating). In this work, we make no distinction between these categories, as per our definition of *co-offending groups*.

The records also 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, including 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 our 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. Here, we regarded each investigation as a single criminal event, regardless of whether it comprised one or multiple crime types.

Network representation and analysis

The relationships between offenders and criminal investigations can be represented as a bipartite network. A bipartite network is a network 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 investigations, and an edge is placed between each offender and the investigations they were involved in. Figure 1 presents an example of a bipartite network with six offenders (1–6) connected to three investigations (a–c).

As a first step in our analysis, it was necessary to identify co-offending groups in line with our proposed definition – i.e. offenders connected to the same

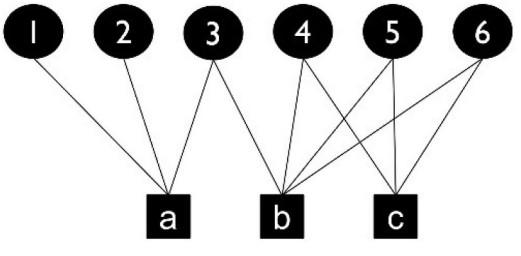

Figure 1. An example of a bipartite network with six offenders (1–6) connected to three criminal events (a–c).

investigation(s). In most studies, this is done by first taking the one-mode projection of the offender-investigation 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 simplest approach is to identify the connected components in the network – i.e. groups of nodes that are disconnected from each other. Alternatively, a more nuanced approach which has been used in other studies (see, e.g. Bahulkar et al., 2018a, 2018b; 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, the use of 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 investigations, which is critical to the definition of a group. Taking the network shown in Figure 1 as an example, the projection of this network would result in the three offenders forming a fully-connected triangle, despite there being no single investigation in which they all featured. 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 common participation in particular crimes.

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 a set of investigations such that all offenders are connected to all investigations. There is redundancy in the connections between nodes in bicliques as the nodes in one mode are all connected to those in the second mode. A biclique is maximal if it does not belong to another biclique; *i.e*. no further offenders or investigations could be added. In practical terms, a maximal biclique represents the largest possible groups of offenders and investigations such that all the investigations involved co-execution by all the offenders. When identifying groups in this way, offenders' participation in crimes does not have to be assumed; it is directly depicted in the graph. Furthermore, using maximal bicliques allows us to have refined information on who participated in which crimes, providing a better estimate of the criminal specialisation of groups.

In Figure 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}). It is worth noting that the construction of maximal bicliques means that they can overlap: G'_2 and G'_3, for example, share both offenders and investigations. A minimum number of investigations can also be set, to consider only those groups involved in two or more investigations; G'_3 would be the only such biclique in this case. We used the

Maximal Biclique Enumeration Algorithm (iMBEA) proposed by Zhang et al. (2014) to extract all the maximal bicliques in our network. The iMBEA combines backtracking[3] and branch-bound[4] 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. We implemented this algorithm using the R package *Biclique* (Lu et al., 2020).

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: (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 $d_{min} = 0$, 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 17 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 et al., 1995; Mazerolle et al., 2000; Piquero et al., 1999), though some examples have used a similar number (Sullivan et al., 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). On the other hand, 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 being of 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 is what we used for this study. Table 1 shows the distribution of crime across the investigations in which two or more co-offenders participated. It also shows the

Table 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 with respect to all crimes (where multiple crimes from the same investigation are counted separately). For example, 56% of the investigations included a crime against private property, while this type of crime represented 40% of the crimes observed in the dataset.

	Proportion of investigations	Proportion of crimes
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

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. 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; S. B. van Mastrigt, 2017; S. van Mastrigt & Carrington, 2019; S. B. van Mastrigt & Farrington, 2009).

As an example, if Group A is linked to two criminal investigations – the first for a drug-related crime and the second comprising another drug-related crime and an assault – then the *d* index will be calculated as $d_A = 1 - \left[\left(\frac{2}{3}\right)^2_{drugs} + \left(\frac{1}{3}\right)^2_{assault} + \ldots + 0^2\right] = 1 - \frac{5}{9} = \frac{4}{9}$. Note that $[\ldots +0^2]$ 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 a burglary). The *d* index for this group would be calculated as $d_B = 1 - \left[\left(\frac{3}{4}\right)^2_{drugs} + \left(\frac{1}{4}\right)^2_{assault} + \ldots + 0^2\right] = 1 - \frac{5}{8} = \frac{3}{8}$. Accordingly, Group B would be considered more specialised than Group A, as $\frac{3}{8}$ is closer to 0.

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 (e.g. Grund & Morselli, 2017) standardise *d* according to the maximum value that could be achieved (which would give $d = 1$ in both aforementioned cases). We do not do this here, with the rationale that diversity is not independent of offence frequency: 3 offences of 3 different types represents greater evidence of diversity, in some sense, than 2 offences of 2 different types.

Other authors have further highlighted the shortcomings of *d* as an estimator of diversity when the number of offences is low. In particular, Francis and Humphreys (2016) showed that *d* tends to underestimate the true level of diversity when there are few offences, essentially because the sample size is too small to accurately quantify the level of diversity across a large number of offence categories. Even more fundamentally, when the number of offences is low, *d* has relatively little granularity: when there are 2 offences, the only possible values for *d* are 0 and 0.5; similarly, there are only 3 possible values when $n = 3$ and 5 possible values when $n = 4$.[5] In such cases, *d* has relatively little discriminatory value between levels of diversity; there is simply too little 'signal'.

In our data, the number of offences for each group is typically low, and so these shortcomings apply. Partly for this reason, and partly because our primary focus is on the high-level distinction between complete specialisation and non-specialisation, we do not perform detailed analysis of the specific values of *e*. For the majority of our analysis, we simply split cases according to whether *d* is zero or nonzero; any further sub-division of the non-zero group would imply a false level of granularity. 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. We compared the groups based on all the crimes detected by the AGO and not only through the sequence of crimes they executed.

Results and discussion

The bipartite co-offending network contained information about 76,697 adult co-offenders linked to 35,604 investigations. Around 85% of the co-offenders were linked to a single investigation, 9% to two, and the rest to three or more investigations. The iMBEA algorithm enumerated 29,195 maximal bicliques with at least two co-offenders connected to a minimum of one investigation – henceforth, we refer to these simply as 'bicliques'. 93% of the bicliques (27,399) involved only one investigation, meaning that the group did not reoffend after the AGO recorded the first investigation during the study period. The remaining 7% (1,796) re-offended and so were associated with more than one investigation. Table 2 presents the distribution of the sizes of maximal bicliques with at least two co-offenders linked to a minimum of two investigations. Of those bicliques, 1,021 had two offenders involved in two criminal investigations, and only 36 (2%) were involved in more than four. The proportion of groups that comprised more than two investigations 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 there was some overlap between co-offending groups, its extent was relatively small. Furthermore, some of these overlaps might be due to the nature of the maximal biclique construction: multiple bicliques can be identified within the same group of offenders.[6] The findings 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; S. B. van Mastrigt, 2017; Warr, 1996, 2002; Weerman, 2003, 2014). However, we should bear in mind the truncated nature of our data when interpreting this finding. The data we used here represents a snapshot of the offenders' criminal careers in a single city. We cannot exclude the possibility that some groups committed additional crimes prior to the study window

Table 2. A cross-tabulation showing the number of maximal bicliques according to the number of offenders and criminal events.

	Offenders					
Criminal events	2	3–5	6–10	11–20	20<	Total
2	1021(57%)	372 (21%)	107 (6%)	48 (2.7%)	7 (0.4%)	1,555 (86%)
3	140 (8%)	39 (2.2%)	17 (1%)	9 (0.5%)	0	205 (11%)
4	24 (1%)	7 (0.4%)	0	0	0	37 (2%)
5	3 (0.2%)	1 (0.1%)	0	0	0	4 (0.2%)
6	1 (0.1%)	0	0	0	0	1 (0.1%)
Total	1,189 (66%)	419 (23%)	124 (7%)	57 (3%)	7 (0.4%)	1796 (100%)

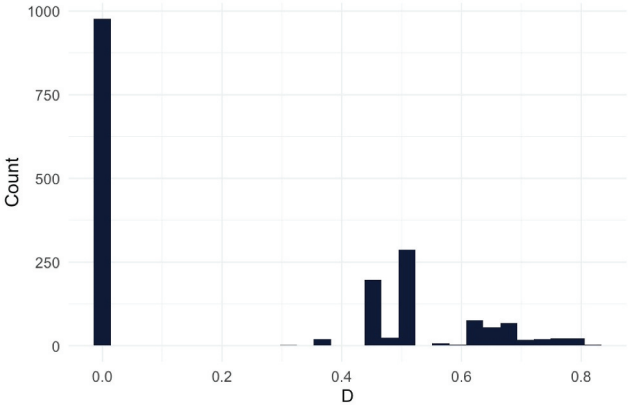

Figure 2. A histogram showing d's distribution. 54% (977) of the co-offending groups were highly specialised (d = 0). For non-specialised groups, d ranged between 0.32 and 0.82. 27% (485) had a d-index between 0.4 and 0.6.

(e.g. it is possible that we observed only a portion of prolific relationships that started before 2008) or that initial contact with the criminal justice system has caused these groups to improve their tactics. For example, deciding to co-offend in a different city could be among the decisions adopted by co-offenders to avoid detection. Our data did not allow us to explore this alternative.

Regarding the central question of this study, Figure 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.

In order 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, we simulated alternative scenarios in which the crime types executed by each co-offending group were selected at random in proportions reflecting the overall distribution of crime types. This represents a situation where the crime types associated with each group are independent of each other, as would be the case if no specialisation effect was present. A similar principle was used to generate a null scenario in previous work by Tumminello et al. (2013) on the similarities between crime types committed by specialists. 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 our data, we would expect the proportion of groups showing complete specialisation ($d = 0$) to be in line with the corresponding proportion for the randomised data.

We ran 1,000 simulations of this process: for each iteration, we kept the original number of bicliques (that is, 1,796 groups that reoffended), offenders per biclique,

Table 3. Distribution of the most common crime types committed by specialised ($d = 0$) and non-specialised ($d \neq 0$) co-offending groups.

	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

criminal investigations, and number of crime types per investigation. We randomly assigned the types of crimes for each investigation 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, we did not observe the proportion of highly-specialised groups by chance ($p < 0.01$).

Table 3 shows the distribution of the most common crime types committed by specialised ($d = 0$) and non-specialised ($d \neq 0$) groups. For specialised groups, 92% of crime types were concentrated into five categories: crimes against private property, 61%; crimes affecting public health, 10%; those related to personal integrity, 9%; public safety, 7%; and crimes against public administration, 6%. For nonspecialised groups, 81% of crimes were concentrated in these same categories but with a different distribution: crimes related to public safety, 28%; private property, 25%; public administration, 11%; public health, 10%; and personal integrity, 7%. 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.

We compared our results 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 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. Our results show that a higher proportion of two-offender bicliques, 64%, were specialised (see Figure 3). Similar to what we noted above, bicliques with two co-offenders who showed specialisation in our data were mainly related to crimes against private property (see Table 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

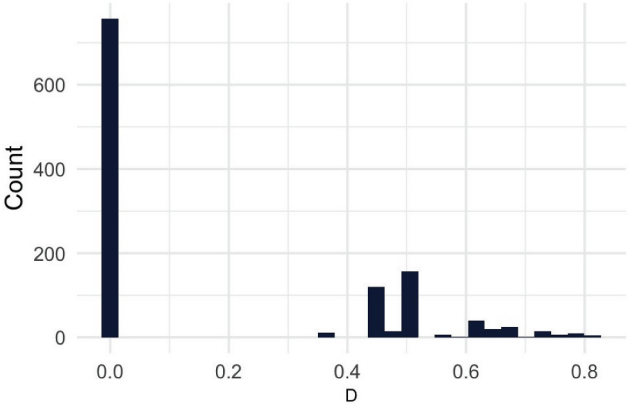

Figure 3. A histogram showing d's distribution in bicliques with two offenders. 64% (761) were highly specialised (d = 0) dyads.

Table 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

directly impacts *d*'s distribution; hence, comparing both studies is not straightforward. However, we can see that roughly half of the groups had some degree of criminal specialisation.

We also analysed the time course of activity by co-offending groups during the study period to see if there were differences between specialised and non-specialised groups. To do this, we used the timestamps attached to each criminal investigation that indicated the date the AGO started investigating a particular event. These timestamps are, of course, an imperfect measure of when the crimes took place: while they will match with the date of occurrence for those crimes in which co-offenders were arrested *in flagrante*, in other cases there is likely to be some delay before the investigation begins. While this means that the values themselves should be interpreted cautiously, there is no reason to expect that the discrepancy should affect the two groups (specialised and non-specialised) differently, and so comparisons are still meaningful. Similar to what we did above, groups were divided between specialists ($d = 0$) and non-specialists ($d \neq 0$), and we measured the number of days between the first and last crime recorded for each group, representing the extent of observed offending.

Figure 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-

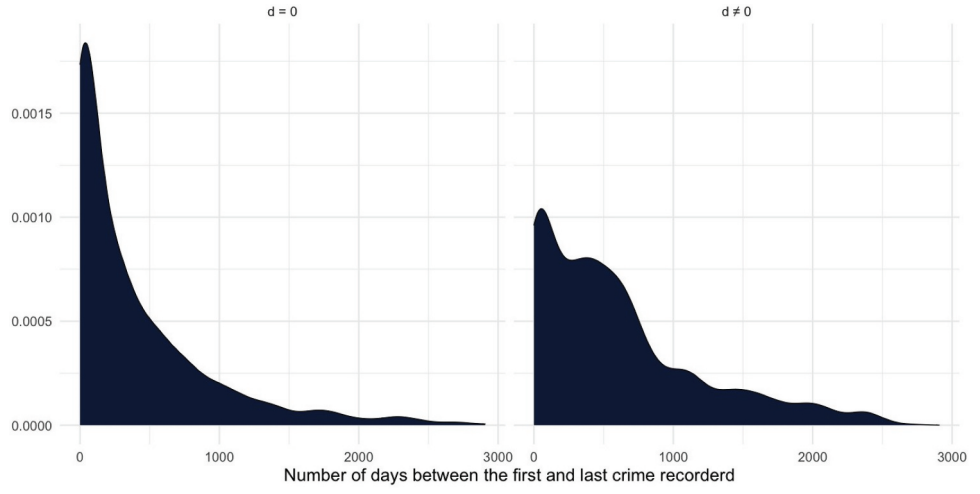

Figure 4. Density plots showing the distribution of days between the first and last crime recorded for highly specialised groups (left) and non-specialised groups (right).

specialised groups. The Mann-Whitney U test suggests the medians are statistically different ($W = 320220$, $p < 0.001$). Hence, specialised groups executed their crimes over a shorter period of time than non-specialised groups. One partial explanation for this is that the two groups participated in different numbers of events – on average, specialised groups participated in 2.09 events, while non-specialised groups participated in 2.23. While this difference is significant ($U = 349044$, $p < 0.001$), however, it is not large enough to account for the differences in intervals. Alternatively, these differences might be attributed to the *spurts of specialisation* displayed by offenders throughout their criminal careers (e.g. Deane et al., 2005; McGloin et al., 2007; Shover, 2018; Steffensmeier & Ulmer, 2017; Sullivan et al., 2006). 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 ought to be tested in future work, using a larger time frame, is that co-offending groups also display spurts of specialisation. By having a larger time frame, we can better understand the behaviours exhibited by co-offending groups. The truncated nature of our data might not reveal the spurts of specialisation exhibited by the groups that were considered in this study as non-specialised.

Conclusions

The work presented here contributes to the scarce literature on the criminal specialisation of co-offending groups. We used official records to build a bipartite network connecting offenders with criminal investigations and extracted maximal bicliques to represent co-offending groups. Our 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. We also observed that 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. A simulation analysis helped us conclude that we did not observe the proportion of highly specialised groups 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.

As far as we know, 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 investigations. Our findings suggest that such groups do 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 difficult for a number of 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 important 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 our 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 on the basis of 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), our data set lacked information on the offenders' level. The availability of socio-demographic data (e.g. age, ethnicity, or prior arrests) in future work could help us 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. Our 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. We could 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 (Sarnecki, 2001; S. B. van Mastrigt, 2017). 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 will 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). Due to the nature of our data, 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 investigations 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 paper aligns with current efforts to exploit network-related concepts to answer crime-related questions (Bichler, 2019; Papachristos, 2011). Here, we used for the first time maximal bicliques as an alternative to identify co-offending groups in a sizeable bipartite network linking offenders and criminal investigations. 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. In this exploratory research, we have demonstrated that studying bipartite networks directly is also a suitable alternative to extract meaningful insights to help us analyse the behaviours displayed by these networks.

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 city and determine if these groups specialise in crimes causing harm to society (Sherman et al., 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*).

In conclusion, our study sheds light on the often-overlooked dimension of criminal specialisation within co-offending groups. The significance of the findings presented here, supported by simulation analyses, highlights that the emergence of highly specialised co-offending groups is not random. This research advances our understanding of criminal behaviour at the group level, and introduces a method that may prove instrumental for criminologists and practitioners in assessing and addressing the specialisation dynamics within co-offending networks.

Notes

1. 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 our research.
2. The AGO anonymised the national identity number of each offender using the MD5 cryptographic hash algorithm. This data did not contain any other piece of information that could be used to reveal the personal identity of those included here. Accordingly, this study received ethical approval.
3. 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).
4. 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)
5. This is because there are only 3 ways to partition 3 offences into different offence types: 1 + 1 + 1, 1 + 2 and 3. The equivalent number for 4 is 5.
6. Consider, for example, a scenario in which 3 offenders co-execute 5 crimes, and 2 of those offenders co-execute a further 5. This would generate 2 maximal bicliques: one with the 3 offenders and the 5 crimes they co-executed, and another with the 2 more prolific offenders and the 10 crimes that they co-executed.

Disclosure statement

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ORCID

Alberto Nieto http://orcid.org/0000-0001-8170-6635

Authors' contributions

All the authors contributed equally to this article. The final manuscript was read and approved by all of them.

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author upon reasonable request.

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