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Offence versatility among co-offenders: A dynamic network analysis

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ABSTRACT

Research examining co-offending has become increasingly popular over the last two decades. Despite this, there remains a dearth of research examining the dynamics of co-offending across time, largely due to limited access to longitudinal data. In the current paper we are interested in explaining crime versatility, and therefore we employ Relational Hyperevent Models (RHEM) to model the conditional probability that a given group of co-offenders engages in one set of crime categories rather than another. Thus, we are analyzing a two-mode network (actors by crime categories) and explain, conditional on a given group of co-offenders, their participation in the set of specific crime types involved in a particular crime event. With respect to co-offending, results reveal that, compared with solo offenders, groups of two or more co-offenders are more likely to engage in crime events involving more than just one crime category. Results suggest that in the context of co-offending both market and property crime show evidence of differential association and social learning. Naïve partners in co-offending partnerships learn the skills and knowledge needed to participate in co-offending involving market and property crime.

Introduction

Research examining co-offending, defined as two or more individuals committing an offence together (Reiss, 1988), has become increasingly popular (e.g., Bright Whelan and Ouellet, 2022; Lantz, 2020, Nieto et al., 2022). Despite this, there remains a dearth of research examining the dynamics of co-offending across time, largely due to limited access to longitudinal data. In addition to data access issues is the challenge of how best to analyse such data over time in ways that do not violate assumptions of longitudinal network analyses (Butts, 2008; Lerner and Lomi, 2023). The current paper leverages a unique, longitudinal dataset and utilises Relational Hyperevent Models (Lerner et al., 2021) to compensate for some of the shortcomings in previous research on co-offending, and to examine the dynamics of co-offending over time.

The existing literature highlights a clear relationship between co-offending and age (see Reiss and Farrington, 1991; Andresen and Felson, 2012), gender (e.g., Bright Whelan and Ouellet, 2022a), inexperience (see Conway and McCord, 2002; Lantz and Ruback, 2017), and the type of crime committed (see van Mastrigt and Farrington, 2009; Andresen and Felson, 2012; McGloin and Piquero, 2010; Morselli et al., 2015). In addition, these factors may also contribute to whether co-offending is an opportunistic and impulsive act, or whether is a planned or even preferred method of offending. Bright, Whelan and Ouellet (2022) found that co-offending rates varied by an offender's sex. Females had higher rates of co-offending for certain crime types (e.g., sexual assault) compared with males. They also found that co-offending was lower for older age groups with the exception of drug offences for which co-offending was more common among older age groups.

Co-offending is a diverse construct, with many factors at play, demonstrated by the many conflicting theories that have been developed to describe how and why co-offending occurs. For example, Weerman (2003) suggested that, compared with solo offending, co-offending appears as an easier and safer option to offenders, whereas Conway and McCord (2002) argue that exposure to delinquent and violent peers contributes to co-offending. Conversely, McGloin and Stickle (2011) argue that chronic offenders may not be as influenced by peers, but this does not reduce the likelihood of co-offending with peers.

Social influence, susceptibility, and exposure to criminal peers have been mooted as potential contributing factors in the formation of co-offending networks (Conway and McCord, 2002; Aral and Walker, 2012; Thomas, 2015). For example, in examining the role of social influence in networks, Aral and Walker (2012) found that influential

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individuals are not susceptible individuals, and, conversely, highly susceptible individuals are influenced by others in the network. Influential individuals are connected to other influential individuals and tend to cluster within a network, strengthening the influence of the network overall (Aral and Walker, 2012).

Co-offending stability and network dynamics

An examination of the social dynamics of co-offending may help to explain how individuals join co-offending networks. For example, Thomas (2015) noted that adolescents whose friends specialised in specific types of crime (such as theft, violence, and substance abuse) had a greater likelihood of specialising in such offences themselves. Whilst this study was not specifically focused on co-offending, this finding provides insight into how peer influence and proximity to crime may facilitate co-offending. A similar dynamic has been observed in co-offending relationships for violent offences, where first time co-offenders who offend alongside a co-offender who has previously committed a violent crime, learn from their accomplice or are influenced by such exposure. Therefore, these offenders have a greater likelihood of committing a violent offence in the future (Conway and McCord, 2002).

Co-offending networks and the relationships within them appear to be built on a foundation of trust and shared characteristics, which facilities their stability over time. For example, Charette and Papachristos (2017) observed that co-offenders who maintain a co-offending relationship over time show increased trust in one another. Moreover, having shared characteristics is key for co-offending networks in building trust (see McCuish, Bouchard and Corrado, 2015; Charette and Papachristos, 2017). Shared characteristics, such as age, race, and gang affiliation may be a key component when recruiting for co-offenders, as well as similar levels of experience, which are also common among co-offenders (see Lantz and Ruback, 2017).

Co-offending and different crime types

The nature and extent of co-offending has been shown to vary across crime types (see Reiss and Farrington, 1991; van Mastrigt and Farrington, 2009; Andresen and Felson, 2012; Morselli, Grund and Boivin, 2015; Bright Whelan and Ouellet, 2022). Property offences appear to be the most common crime type involving co-offending (Andresen and Felson, 2012; Ouellet et al., 2013; Morselli, Grund and Boivin, 2015). Other common crime types include some financial offences and market offences (Andresen and Felson, 2012), as well as robbery, arson, burglary, and motor vehicle theft (Reiss and Farrington, 1991; van Mastrigt and Farrington, 2009). Sexual offences and fraud are less likely to involve co-offending (Reiss and Farrington, 1991; van Mastrigt and Farrington, 2009). Age and level of experience may be important factors in the types of crimes co-offenders engage in. As Reiss and Farrington : 375) (1991) point out, burglary and robbery offences are commonly committed by older individuals, suggesting age is a key factor in co-offending for these crime types. Bright et al. (2022) found that co-offending rates varied substantially by crime type. Co-offending was much more common for some crimes than others, and offenders arrested for homicide were more frequently observed in the core of the co-offending network.

There are few studies exploring co-offending and trends across crime types (see van Mastrigt and Farrington, 2009), as most co-offending research examines co-offending as it occurs for specific offences. Little is known about how co-offending across crime types changes over time, largely due to the lack of longitudinal data (see Lantz and Ruback, 2017). Understanding longitudinal trends in co-offending and whether co-offending diversifies over time is vital for providing insight into criminal careers as well as for informing the development of policy to address co-offending. The current study addresses this significant gap in the research literature on co-offending.

Co-offending dynamics over time

In general, co-offending relationships appear to be short-lived (see Reiss and Farrington, 1991; McGloin et al., 2008; Morselli et al., 2015; Charette and Papachristos, 2017). Most co-offending relationships cease after the first co-offence (Reiss and Farrington, 1991; Charette and Papachristos, 2017), although it is not uncommon for more prolific offenders to retain familiar accomplices (McGloin et al., 2008). Charette and Papachristos (2017) described the importance of trust in the longevity of co-offending relationships; they noted that individuals who paired with a co-offender they trusted tended to remain loyal to each other and continued to co-offend together. Moreover, they found that the more co-offenders offended together, the stronger and longer lasting the co-offending relationship over time (Charette and Papachristos, 2017).

There has been conjecture that co-offending in general widens criminal experience and exposes individuals to greater opportunities (McGloin and Stickle, 2011; Andresen and Felson, 2012). Indeed, some findings suggest that co-offenders who maintain their co-offending relationship tend to expand their repertoire to a wider range of crime types (e.g., Grund and Morselli, 2017). McGloin and Piquero (2010) found that co-offending networks that were more intertwined exhibited wider variety of crime types committed. They attributed this to increased availability of different skillsets, and broader knowledge and range of opportunities within a more diverse network. Given these results, more research is needed to disentangle the relationship between co-offending and offence versatility.

While there is a significant lack of longitudinal studies examining trends in co-offending over time, it is well understood that co-offending does not remain static (see Ouellet et al., 2013). However, what is missing is an understanding of *how* co-offending changes over time. An exploration of the dynamics of co-offending over time, in particular with respect to changes in criminal versatility, will facilitate a deeper understanding of how social influence operates within co-offending networks. The aim of the current paper is to examine criminal versatility among co-offenders across time. Specifically, we explore the following research question: to what extent does participation in co-offending increase criminal versatility across offence categories over time?

Relational Hyperevent Models (RHEM)

Relational Hyperevent Models (RHEM) offer advantages over other network analysis approaches for the study of co-offending networks. Importantly, RHEM can be used to analyze data on co-offending events without projection to a one-mode network and without the need to aggregate events over (what are typically arbitrary) time intervals. In a nutshell, RHEM can specify and estimate for every set of nodes and every point in time a separate *event rate* (i.e., the expected number of events in which a given set of nodes participates, also known as *hazard rate* or *intensity*) based on exogenous or endogenous covariates. RHEM has been applied, among other types of models, to explain the propensity of actors to co-participate in meeting events (Lerner et al., 2021) or the propensity of researchers to co-author a scientific paper (Lerner & Hâncean, 2022). RHEM has been used previously to analyze co-offending networks, predicting a group's hazard to co-offend at a given point in time (Bright et al., 2023). As the current paper is interested in explaining crime versatility, we employ RHEM to model the conditional probability that a given group of co-offenders engages in one set of crime categories rather than another. Thus, we are analyzing a two-mode network (actors by crime categories) and explain, conditional on a given group of co-offenders, their participation in the set of specific crime types involved in a particular crime event.

Method

Sample and data

De-identified data were collected for all offences recorded by the New South Wales (NSW) Police across a five-year period (2011–2015) for the metropolitan area of Sydney, Australia.[1] The data is for all recorded crime events and all persons associated with each crime event across the Sydney metropolitan areas, covering a population of approximately 4.4 individuals (based on 2011 census data; see https://www.abs.gov.au/census). The data was collected from the NSW Police Computerised Operational Policing System (COPS), via the Enterprise Data Warehouse. Records were extracted on the 15 June 2017. The dataset includes selected information on all persons charged, that is, issued with a Court Attendance Notice, in relation to offences occurring in one of three NSW Police Force Metropolitan regions between 2011 and 2015 (Central, North West, and South West). Data were included where either the charge date, incident start or end date, or event reported date was between 2011 and 2015, and where the record is classified as involving an "Event".[2] COPS generates unique reference numbers for data based on whether a record is classified as involving an "Event" or an "Incident", that is, whether it is part of a broader course of conduct involving the same person or a group of persons. COPS also generates a unique reference number for each individual. These reference numbers link different individuals involved in the same Event, which we assume to be co-offenders. For each individual recorded as part of the incident, information on their date of birth and sex is provided. For each incident or event, information on the offence-type, date, and location is provided. The project received ethics approval from the University of New South Wales Panel.[3]

Coding and analysis

To prepare the data for analyses three main data cleaning processes were performed. First, we retained data only for the years 2011–2015. Second, for offenders who had more than one date of birth on record, we took the individual's lower year of birth. Third, we removed all public order offences, traffic and vehicle regulatory offences, and offences against government procedures. We removed public order offences because they often involved large groups of offenders arrested at the same time / event, but given their nature (i.e. large protests) we could not be confident the offenders were actually collaborating in the offence. Traffic offences were removed as they accounted for a high volume and are typically solo offences. Offences against government procedures accounted for a very small number of offences so they were also excluded.

Next we used the Australia and New Zealand Standard Offence Classification system (ANZSOC), which provides a uniform national framework for classifying offences across Australia and New Zealand, to place all offences into four categories. All remaining ANZSOC offence groups (i.e., following removal of the offences listed above) were allocated into four non-overlapping crime categories: (1) Violent crimes: crimes against the person (e.g., assault, sexual assault, murder, attempted murder); (2) Property crimes: crimes against property (e.g., malicious damage, break and enter, theft, robbery); (3) Market crimes: crimes committed within illicit markets (e.g., drug trafficking, importation of illicit drugs, prostitution)[4]; (4) Other crimes: crimes that did not fit within the above three categories (e.g., breaches of criminal justice orders, offences against justice procedures, noise pollution offences, forgery and fraud). These four crime categories have been used in previous research on co-offending networks (Morselli et al., 2015) and form the basis of our analysis.

Using Relational Hyper Event Models, we model offending and co-offending as 'hyperevents'. That is, one offending incident is considered to be a single observation even if it involves more than one offender. Moreover, each incident can involve any combination of the crime categories Violent (V), Market (M), Property (P), and Other (O) (between one and four categories). Thus, an observation has the form $(\{a_1, \ldots, a_k\}, \{c_1, \ldots, c_p\})$ where the first set are the k actors participating in the incident (at least one, up to any number) and the second set are the crime categories that are involved (at least one, up to four).

Models were conditioned on the set of actors that were co-arrested. That is, we take it for granted that the given actors offend or co-offend in the same incident and explain which crime categories are involved in that incident. For each incident, there are exactly 15 different possible combinations of the four crime categories;$2^4 - 1 = 15$ different subsets (excluding the empty subset). Given that the subsequent crime incident involves the actors $\{a_1, \ldots, a_k\}$, all models in this paper seek to explain the relative probabilities of these 15 combinations of crime categories. By doing so we can determine the extent to which actors commit the same type of crime in future offending, under which conditions their offending involves more than one crime category, and under which conditions they extend their "portfolio" of crime types (that is, commit types of crimes they have not committed previously). We are especially interested in the effect of multi-actor crimes (i.e., co-offending) on these outcomes. In Fig. 1 we show an illustrative example in which circles represent actors and rectangles represent crime categories. At time t1, actors a and b co-offend in an incident involving market crimes (M), at time t2, actors b and c commit property crimes (P) and violent crimes (V) while co-offending. At time t3, we observe that actors c and d co-offend. Models used in this paper seek to predict which set of crime categories are involved in this incident committed by c and d (indicated by the question mark). Hypothetical predictions for this stylized example would be that c and d are likely to commit property crimes and/or violent crimes since c already has experience with these crime categories. Another hypothetical prediction would assume social contagion which may make it more likely that c and d commit market crimes since c's past

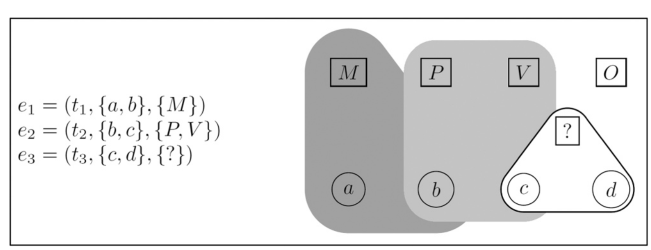

Fig. 1. Illustrative example of models that include co-offending across different crime types.

[1] Approval from NSW Police was provided on 8 September 2016.

[2] A COPS "Event" consists of one or more "Incidents" that are related to the same unique occurrence (i.e. that are part of a course of conduct), and are committed by the same person or group of persons; are part of actions committed simultaneously or in sequence over a short period of time or which come to light as a result of an investigation; are part of interrelated actions, that is, where one action leads to the other or where one is the consequence of the other(s); or that involve the same action(s) repeated over a long period of time against the same victim(s) but only come to the attention of the police at the one point in time.

[3] Panel B: Arts, Humanities and Law, approval # HC16141; The first author was employed at UNSW at that time. The project subsequently received approval from the human ethics committee at Flinders University.

[4] Offences involving only the use and possession of illicit drugs were not included in the market crime category and were instead captured by the 'other crime' category. The market crime category is intended to capture crimes involving participation in illicit markets as a seller, dealer or trafficker of contraband or illicit commodities.

collaborator b already has experience with this type of crime.

Model and effects

Our empirical data comprises a list of incidents $(t_1,A_1,C_1),.,(t_n,A_n,C_n)$.

For the i'th incident, t_i denotes the start time of the incident (given by the day), $A_i = \{a_{i1},.,a_{ip_i}\}$ denotes the group of co-offenders (where the number of co-offenders, p_i is at least one and theoretically unbounded from above), and $C_i = \{c_{i1},.,c_{iq_i}\} \subseteq \{V,P,M,O\}$ is the set of crime categories involved in the incident (the number of crime categories, q_i, is at least one and at most four). We let C^* denote the set of all non-empty subsets of $\{V,P,M,O\}$ and let A^* denote the set of all actors.

Models used in this paper explain the selection of the crime categories C_i, conditional on the observed group of co-offenders A_i as a function of a vector of explanatory variables $x_{ti}(A_i,C_i)$. These variables quantify aspects that might explain whether C_i is a suitable or unsuitable choice of crime categories for the group of co-offenders A_i at time t_i. An example is given by a measure of previous (i.e., before time t_i) experience of the actors in A_i with the crime categories in C_i. In general, the variables $x_{t_i}(A_i, C_i)$ may be functions of exogenous node covariates and/or of the history of prior incidents at time points $t_j < t_i$; see the definitions of variables used in this paper below.

The partial likelihood, evaluated at parameter vector β, is given by the following equation (compare Perry andWolfe, 2013 and Lerner and Lomi, 2023).

$$L(\beta) = \prod_{i=1}^{n} \frac{\exp\left[\beta^T x_{t_i}(A_i, C_i)\right]}{\sum_{C \in C^*} \exp\left[\beta^T x_{t_i}(A_i, C)\right]}$$

The term $\exp\left[\beta^T x_{t_i}(A_i, C)\right]$ is the *relative risk* that actors A_i choose the set of crime categories C and the partial likelihood function compares the relative risk of the observed set C_i with the sum of the relative risks over all possible choices of crime categories $C \in C^*$. This model is equivalent to a multinomial choice model, where the group of actors A_i engages in a set of crime categories C_i out of the set of 15 possible combinations of crime categories C^*. We compute the explanatory variables x with the eventnet[5] software (Lerner et al., 2021) and estimate the maximum likelihood parameters with the coxph function in the R package survival (Therneau, 2015).

Effects

Below we define explanatory variables $x_t(A,C)$ used in this paper. Note that some of these variables are independent of the current time t and some are independent of the set of co-offending actors A. We nevertheless keep the subscript t and the argument A in the definition of all explanatory variables to employ a consistent notation.

Properties of the set of crime categories

For a crime category $c \in \{V,P,M,O\}$, we get a binary indicator variable (e.g., "*Incidents involving Market Crimes*") that is one if and only if the set of crime categories C contains c:

Incidents involving $c_t(A,C) = 1\{c \in C\}$.

where $1\{\cdot\}$ is the indicator function that is one if the argument is true and zero if the argument is false.

The three indicator variables for V, P, and M control for varying baseline frequencies of these three types of crimes; the "other" category (O) is taken as the baseline category.

We also include the pairwise interactions among crime categories V, P, and M (e.g., "*Incidents involving Market and Property crimes*") to account for whether any pair of these categories co-appears in the same incident more or less frequent than suggested by their baseline frequencies.

The variable *Incidents with multiple crime categories*$_t(A,C) = 1\{|C| > 1\}$ is an indicator that is one if the incident involves more than just one crime category and *Number of crime categories of incidents*$_t(A,C) = |C|$ gives the number of crime categories (a value ranging from one to four). These two variables control for the relative (in-)frequency of incidents involving a higher number of crime categories (i.e., "diversified incidents").

Group composition interacted with properties of the set of crime categories

The next family of effects interacts properties of the group of co-offending actors A (such as their average age) with some of the properties of the set of crime categories C defined above.

Our empirical data include as demographic variables the sex of actors (binary variable *female*) and their age, given in years. From these demographics, we get variables for the group composition:

$$\text{Ratio of females}_t(A, C) = \sum_{a \in A} \frac{\text{female}(a)}{|A|}$$

$$\textit{Average age}_t(A, C) = \sum_{a \in A} \frac{age(a)}{|A|}$$

which we interact with the indicators of the three crime categories V, P, and M to control for preference or reluctance of females (or older persons, respectively) to engage in the respective crime categories.

Moreover, we interact the binary variable *Group incident*$_t(A,C) = 1\{|A| > 1\}$ with the indicators of whether the incident involves more than one crime category (*Incidents with multiple crime categories*) and with the number of crime categories involved. These interactions test whether groups engage more or less often in diversified incidents than solo offenders.

Familiarity and familiarity differences with crime categories.

The variable *Previous experience with crime categories* for a set of co-offenders A and a set of crime categories C quantifies the average prior experience of the actors in A with the crime categories in C. For a crime category $c \in \{V,P,M,O\}$, an actor $a \in A^*$, and a point in time t, let *prior*$_t(a,c)$ be a binary indicator that is one if actor a participated in at least one incident that involves c at a prior time $t' < t$. In formulas.

$$prior_t(a,c) = \mathbf{1}\{\exists j\colon t_j < t \wedge a \in A_j \wedge c \in C_j\}\cdot$$

The variable *Previous experience with crime categories*$_t$ (A,C) is defined as

$$\textit{Previous experience with crime categories}_t = \sum_{a \in A, c \in C} \frac{prior_t(a, c)}{|A| \cdot |C|}$$

Moreover, for a crime category $c \in \{V,P,M,O\}$ and a group of actors A that contains at least two members, we define the groups heterogeneity in prior experience with c (e.g., denoted as "*Heterophily in Market Crimes*") by.

$$\text{Heterophily in } c_t(A, C) = \sum_{a, a' \in A} 1\{c \in C\} \cdot \frac{|\text{prior}_t(a,c) - \text{prior}_t(a',c)|}{|A| \cdot (|A|-1)/2}$$

(If $|A| = 1$, we define the heterophily variable to be zero since an actor cannot have a different experience than herself.) In other words, if the focal set of crime categories C contains c, the above variable is the fraction of pairs of actors in A that have a different previous experience with respect to c. This variable is a measure of heterogeneity of the group. If the associated parameter is positive, it would reveal that group incidents tend to mix experienced with inexperienced members; if the associated parameter is negative, it would reveal that groups tend to be

[5] https://github.com/juergenlerner/eventnet

homogeneous with respect to experience in the focal crime category. The variable "*Heterophily in crime categories*" is the sum of the heterophily variables over the four crime categories.

Social contagion (commit crime category of past collaborator)

A final explanatory variable quantifies to what extent the past collaborators of the focal set of actors have prior experience with the focal crime categories. As an example, consider Fig. 1 and assume that the question mark in the third incident stands for "M" (market crimes). None of the actors c and d has any prior experience with market crimes. However, c's past collaborator b has prior experience with M. The variable defined in this paragraph tests whether this precondition leads to an increased probability that c commits market crimes in the third incident.

For two different actors $a, a' \in A^*$, and a point in time t, let $prior_t(a,a')$ be a binary indicator that is one if a and a' co-participated in at least one incident at a prior time $t' < t$. In formulas.

$$prior_t(a,a') = 1\{\exists j: t_j < t \wedge a \in A_j \wedge a' \in A_j\} \cdot$$

The variable *Committing crimes of collaborators*$_t(A,C)$ quantifies to what extent actors in A have previously collaborated with actors who have prior experience with crime categories in C. In formulas:

$$Committing\ crimes\ of\ collaborators_t(A,C) = \sum_{a\in A, c\in C, a'\in A^*} \frac{prior_t(a,a')\cdot prior_t(a',c)}{|A|\cdot|C|}$$

Results

Of a total of 333,326 crime events, 12,598 (3.78%) involved market crimes, 84,607 (25.38%) involved property crime, 115,159 (34.55%) involved violent crimes, and 160,120 (48.04%) involved other types of crimes not covered by the main three categories. Note that a single crime event can involve multiple crime categories, so the total number of crime categories is higher than the aggregate number of events. Of 333,326 crime events, 322,286 (96.69%) were solo offences and 11,040 (3.32%) involved co-offending.

At the individual level, frequency of offending is displayed in Table 1, showing that while 77,560 offenders committed a single offence, 16,131 offenders committed two offences and one offender committed 80 offences over the time period. The mean number of offences committed by individuals was 2.11 (SD = 2.80127). From the table we can calculate that a total of 38,325 offenders committed more than two offences. 96.69% of incidents were conducted by a sole actor, while 2.76% of incidents were conducted by a pair of actors. Table 2 displays the number of offenders involved across crime events. The average number of offenders arrested per crime event was 1.04 (SD=0.25).

Results of all three models are summarized in Table 3. The three models are displayed in the three columns on the right side of the table. For completeness, we also generated results for these three models including effects for age and sex, but the results were not found to be different when age and sex were included / excluded. Therefore, we present the three models excluding effects for age and sex in Table 3. For reference, we include the full models, including effects for age and sex, in an Appendix. We also include a note on robustness checks in the Appendix.

Model 1

Model 1 includes indicators of whether the crime event involved market crimes, property crimes, or violent crimes, as well as pairwise combinations of these crime categories. It includes an indicator of whether the crime event involved more than one crime category, the

Table 1
Frequency of Offending.

Number of offences	Frequency (Number of offenders)
1	77,560
2	16,131
3	7046
4	4200
5	2714
6	1883
7	1383
8	1015
9	743
10	580
11	488
12	412
13	306
14	265
15	206
16	155
17	135
18	118
19	102
20	59
21	64
22	41
23	33
24	28
25	33
26	16
27	25
28	11
29	16
30	19
31	20
32	9
33	8
34	14
35	7
36	8
37	6
38	2
39	2
40	1
41	2
42	2
45	2
47	1
49	3
50	5
56	1
65	1
72	1
73	2
80	1
Total	115,885

Table 2
Group size per event/incident.

Group size	Frequency (Number of crime events)
1	322,286
2	9220
3	1292
4	354
5	89
6	49
7	21
8	5
9	6
10	1
11	1
12	1
15	1
Total	333,326

Table 3
Model results (excluding age and sex).

Effects	Model 1	Model 2	Model 3
Incidents Involving Market Crimes	-2.618 (0.010)***	-2.429 (0.010)***	-2.396 (0.010)***
Incidents Involving Property Crimes	-0.697 (0.005)***	-0.645 (0.005)***	-0.638 (0.005)***
Incidents Involving Violent Crimes	-0.386 (0.004)***	-0.329 (0.004)***	-0.322 (0.004)***
Incidents with multiple crime categories	-1.469 (0.030)***	-1.480 (0.030)***	-1.458 (0.030)***
Number of crime categories of incidents	-1.061 (0.028)***	-1.039 (0.028)***	-1.073 (0.028)***
Incidents involving Market and Property Crimes	0.625 (0.032)***	0.463 (0.032)***	0.514 (0.032)***
Incidents involving Market and Violent Crimes	-0.806 (0.047)***	-0.923 (0.047)***	-0.902 (0.047)***
Incidents involving Property and Violent Crimes	-0.024 (0.018)	-0.075 (0.018)***	-0.050 (0.018)**
Group incidents with multiple crime categories	0.527 (0.067)***	0.634 (0.067)***	0.588 (0.067)***
Number of crime categories of group incidents	0.923 (0.053)***	0.700 (0.054)***	0.946 (0.053)***
Previous experience with crime categories		0.752 (0.005)***	0.742 (0.005)***
Heterophily in crime categories		-1.158 (0.052)***	
Heterophily in market crimes		3.383 (0.115)***	
Heterophily in property crimes		1.546 (0.056)***	
Heterophily in violent crimes		0.807 (0.060)***	
Group incidents previous experience with crime categories		1.123 (0.040)***	0.788 (0.036)***
Committing crimes of collaborators			0.226 (0.007)***
AIC	957425.400	926776.540	927041.907
Num. events	332899	332899	332899
Num. obs.	4993485	4993485	4993485

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

number of crime categories, and the interaction of these two variables with the "group incident" indicator (i.e., whether the crime incident involved co-offending). Results reveal that market crimes are less frequent (negative parameter of "Incidents Involving Market Crime") than property crimes (negative parameter of "Incidents Involving Property Crime") which are less frequent than crimes involving violence (negative parameter of "Incidents Involving Violence") which are, in turn, less frequent than "other" types of crimes (we use this "other" crime category as a baseline category). The "other" category of offences, as described earlier, were all offences that did not fit into the three categories. The other category included offences such as environmental offences, breaches of justice orders (e.g., breaches of bail), and occupational health and safety breaches. The interaction effects for crime types reveal that market crimes and property crimes co-occur more often (positive parameter of "Incidents Involving Market and Property Crimes") than suggested by their baseline frequencies. Market crimes and violent crime co-occur less often than suggested by their baseline frequencies (negative parameter of "Incidents Involving Market and Violent Crimes"). The interaction of property crime and violence is not significant (these two categories co-occur about as often as suggested by their baseline frequencies).

Results further suggest that crime events including combinations of crime categories are rare (negative parameter of "incidents with multiple crime categories") compared with crime events involving only one crime category. Further, the number of crime categories involved in a crime event has an additional negative effect (negative parameter of "number of crime categories"). That is, combinations of crime categories involving four crime categories are less likely than those involving three crime categories, which are less likely than those involving two crime categories, which are less likely than single-category crime events.

With respect to co-offending, we find that groups of two or more co-offenders are more likely (compared with solo offenders) to commit offenses involving more than one crime category (positive effect "Group incidents with multiple crime categories"). We also find that co-offenders are more likely than solo offenders to commit offenses involving larger numbers of crime categories (positive effect of "number of crime categories of group incidents"). It does not yet say anything about whether groups are more likely to commit 'new' types of crimes (crime categories they have no previous experience with) or whether co-offenders have the potential to introduce co-offence partners to new types of crimes (i.e., social contagion). We consider these possible offending dynamics in the other models discussed below.

Model 2

In Model 2 (see Table 3), we include a variable encoding previous experience of individuals with each of the crime categories included in each crime event. The indicator is equal to 1 if all participants have previous experience with all crime categories involved in the new crime event. By 'previous experience', we mean that the individual has been involved in crime events previously that included a particular crime category (e.g., violent crime). If, for example, the new crime event involves three participants and two crime categories (e.g., market and property) and all three have been involved in previous market crime events but only two participants have been part of previous property crime events, then the previous experience variable is 0.83 or 5/6 (see above for a precise definition).

The heterophily of co-offenders measures the extent to which co-offenders have differing previous experience with a given crime category. For example, the variable "heterophily in violent crimes" captures, for collections of crime categories that involve violent crimes, the difference in familiarity among the co-offenders with respect to violent crimes. We include analogous variables for property crimes ("heterophily in property crimes") and market crimes ("heterophily in market crimes"). The variable "heterophily in crime categories" (without a crime category label) gives the difference in previous experience across all crime categories. Note that these variables can only be non-zero for group incidents. They are necessarily zero for solo incidents since there can be no variation of previous experience with crime categories at the individual level. Therefore, any effect of the heterophily variables is necessarily restricted to dynamics associated with co-offending rather than solo offending.

Results reveal that actors tend to be involved in crime events that include familiar crime categories (i.e., those they have committed previously) as can be seen from the positive coefficient of "previous experience with crime categories". For crime events involving co-offending, this familiarity effect is even stronger (i.e., positive coefficient of "group incidents previous experience with crime categories"). The heterogeneity effects for the three crime categories (property, violent and market) are all positive. The strongest effect was found for market crimes, followed by property crimes, with the weakest effect for violent crimes. The effect for heterophily in all crime categories is negative which indicates that for "other" crimes (i.e., crimes that do not fit in any of the three primary crime categories) previous criminal experience of co-offenders seems to be homogeneous. We provide a more detailed, example based, discussion of the heterophily effect below.

To supplement the above analyses, we also conducted analyses using a variant of the "previous experience" variable in which we considered the number of prior events involving specific crime categories rather than the binary indicator whether an actor has any prior experience with a given crime category. In these analyses, we did not find any substantive difference to the findings obtained with the binary version of prior experience.

Model 3

In Model 3 (see Table 3) we include a variable ("committing crimes of collaborators") encoding whether actors tend to commit offenses that involve crime categories that have been committed in the past by actors with whom the focal actors have co-offended previously. To further illustrate this effect, assume that actor B has participated in a past incident that involved crime category X. Also assume that actors A and B have co-offended in the past (in an incident that involves any collection of crime categories). By the positive coefficient of "committing crimes of collaborators", this precondition makes actor A more likely to commit an offense that involves crime category X. This is a closure effect in a two-mode network (actors by crime type).

Heterophily effects

To illustrate the findings regarding the heterophily effects in relation to previous experience with crime categories, we use the following example. Assume that there are three different groups of co-offenders, each comprising two actors: A1 = {a1, a′1}, A2 = {a2, a′2}, and A3 = {a3, a′3}. Below we illustrate quantitatively how the effects for the "previous experience" and "heterophily" variables impact the predicted relative probabilities that these three groups commit the set of crimes C= {M}, that is, incidents involving market crimes (and only market crimes). Assume that at the current time *t*, actors a1, a′1, and a2 have previously committed market crimes but that actors a′2, a3, and a′3 have not previously committed market crimes. By the definition of the "previous experience" variable we get at time t.

previous experience (A1,C) = 1.

previous experience (A2,C) = 0.5.

previous experience (A3,C) = 0.

The coefficient associated with "previous experience" in Model 2 is 0.752, from which we conclude that the "previous experience" effect alone (that is, disregarding all the other effects in the model) multiply the relative risk that the group of co-offenders A1 selects the set of crime categories C= {M} by a factor of exp(1 *0.752)= 2.12. That is, an increase of 112%. For the group of co-offenders A2, this factor is exp (0.5 *0.752)= 1.46. That is, an increase of 46%. For the group of co-offenders A3, this factor is exp(0 *0.752)= 1 indicating that for this group, previous experience with the crime categories has no effect at all (indeed, A3 have no previous experience with market crimes). Note that the preceding discussion ignores all other model effects, notably the negative baseline effect that market crimes are the least frequent type of crimes in our data with a coefficent of − 2.429. Thus, market crimes are a rare choice for all groups, but for group A3 they are an even more implausible choice than for A2 and for A2 they are a more implausible choice than for A1.

To illustrate the additional effect of the heterophily variables, we note that for the specific set of crime categories C= {M} the variable "heterophily in crime categories" is identical to "heterophily in market crimes" and that the values of these variables for the three groups are: heterophily (A1,C) = 0; heterophily (A2,C) = 1; heterophily (A3,C) = 0.

To understand where these values come from, note that both actors in A1 have the same previous experience with market crimes, both actors in A3 have the same previous experience with market crimes, and actors in A2 have differing experience with market crimes.

For Model 2, the coefficient of "heterophily in crime categories" is − 1.158 and the coefficient of "heterophily in market crimes" is 3.383, leading to a net effect for market crimes of 3.383 − 1.158 = 2.225. Thus, considering the joint effect of the "previous experience" and "heterophily" variables (disregarding all other effects in Model 2), we find that these two effects multiply the relative risk that the group of co-offenders A1 selects the set of crime categories C= {M} by a factor of exp (1 *0.752 + 0 *2.225)= 2.12 (which is the same factor that we get by the previous experience effect, ignoring the heterophily effect). For the group of co-offenders A2, this factor increases to exp(0.5 *0.752 + 1 *2.225)= 13.48 (which is a much larger factor compared with results when we ignore the heterophily effect and this factor is even larger than for group A1). Finally, for the group of co-offenders A3, this factor is exp (0.5 *0.752 + 1 *2.225)= 1.0 (the same as we found previously).

To summarise, the heterophily effect renders market crimes a much more plausible choice for the group of co-offenders (A2) that has mixed previous experience with market crimes. Again, we emphasize that there are other effects in the model, reducing the relative probability that actors will choose to engage in market crimes compared to choosing other types of crimes. This discussion is only about the joint effects of previous experience and heterophily.

We turn now to a discussion of the heterophily effects for property crimes and violent crimes. The coefficient of "heterophily in property crimes" is 1.546, which together with the coefficient of "heterophily in crime categories" (−1.158) leads to a net effect of 1.546 − 1.158 = 0.388. Constructing a similar example as above (systematically substituting 'P′ for 'M′), we obtain for the group of co-offenders A1 a relative risk factor for choosing property crimes equal to exp(1 *0.752 + 0 *0.388)= 2.12 (exactly the same factor as in the previous example for market crimes). For the group of co-offenders A2, this factor is exp(0.5 *0.752 + 1 *0.388)= 2.15, implying that the joint effect of previous experience and heterophily for group A2 (having mixed experience with property crimes) is almost identical with their joint effect for group A1 (in which both members have previous experience with property crimes). Finally, for the group of co-offenders A3, this factor is exp(0 *0.752 + 0 *0.388) = 1, since both members have no previous experience with property crimes. Qualitatively, the joint effect of previous experience and heterophily imply that groups A1 (both members have previous experience with property crimes) and A2 (with mixed previous experience in property crimes) have about the same relative risk to select property crimes when co-offending. But for group A3 (having no previous experience with property crimes) it is rather implausible that actors will choose this type of crime.

Finally, we turn briefly to violent crimes. We note that the net effect of heterophily in violent crimes is 0.807 − 1.158 = −0.351. Thus, the heterophily effect implies that co-offending groups tend to have homogeneous experience with the violent crime category. For a group having mixed previous experience, choosing violent crimes would be about as implausible as for a group having no previous experience with violent crimes.

Discussion

Offending diversity and criminal versatility

With respect to co-offending, results reveal that, compared with solo offenders, groups of two or more co-offenders are more likely to engage in crime events involving more than just one crime category. This finding supports previous findings that co-offending can be more harmful compared with solo offending (e.g., Lantz and Kim, 2019; Carrington, 2002; Felson, 2003). Results suggest that co-offenders are more criminally versatile compared with solo offenders. That is, co-offenders commit a wider range of crime categories compared with those who only offend on their own. This finding is also consistent with previous research finding that individuals who engage in co-offending commit a greater number of offences and at more serious levels (Hindelang, 1976; Felson, 2003; Sarnecki, 2001; Warr, 2002; Zimring, 1981) and that co-offending has the potential to further embed individuals in criminal lifestyles, including by expanding and deepening offending repertoires (Andresen and Felson, 2012; McGloin and Nguyen, 2014).

Offending heterophily

For co-offending we found a positive heterophily effect for type of crime. The strongest effect was for market crime, followed by property crime and violent crime. Co-offending tends to bring together a combination of co-offenders who have previous experience in each crime category with co-offenders who are inexperienced (or have no experience) with that particular crime category. This is especially the case for property and market crime where the effects are more substantial compared with violent crime. Thus, the positive effect of "heterophily in market crimes" implies that co-offending groups tend to bring together experienced with inexperienced members where supposedly the experienced ones initiate inexperienced co-offenders in committing a new type of crime. This is also likely due to the relational features of market-based crimes. For example, offenses related to the supply and distribution of illicit goods involve larger and more diverse co-offending networks, across a broad division-of-labor, which necessitates more interaction among offenders (e.g., manufacturing / importing drugs, supplying drugs, selling drugs, purchasing drugs, laundering proceeds; e.g., Bright and Delaney, 2013; Malm and Bichler, 2013; Malm et al., 2011).

Offending and social contagion

The finding also supports the notion that offenders learn new types of crime (crimes they have not engaged in previously) via exposure / contagion. That is, criminal versatility appears to be learned through contact with other offenders via co-offending relationships. Our results provide more revealing insights into the nature of the social processes at work in co-offending dynamics over time. We found that actors show a tendency to commit offences associated with crime categories that have been committed in the past by those with whom they have previously co-offended. This suggests processes of learning or social contagion resulting from past criminal collaborations. Results reveal evidence for a type of triadic closure that suggest offenders learn from criminal collaborators in what can be considered a form of social contagion. In particular, the variable "committing crimes of collaborators" measures "learning" or "contagion" from past co-offending collaborators. The social processes involved are akin to 'differential association' and social learning (e.g., Sutherland, 1973; Akers, 1985). These theoretical accounts for crime suggest that much like other behaviour, criminal behaviour is learned behaviour and that social interactions with criminally inclined individuals plays a significant role in the development of criminal motivations and repertoires. Differential association theory argues that criminal behaviour is learned and adopted through relationships or ties with others and that such relationships facilitate the transmission of behaviour, knowledge, motivation and attitudes. One interpretation of our results is that co-offenders learn from each other the knowledge and behaviours required to engage in crimes with which they have little or no prior experience.

Offending familiarity and heterophily

The finding that group offenses tend to involve more crime categories (compared with solo offenders) is best interpreted in conjunction with the stronger effect of familiarity in group offenses. Solo offenders are more likely to engage in one (or at least, a smaller number of) crime categories, but they may change that category from incident to incident more often than the group offenders. In contrast to solo offenders, co-offenders are more likely to engage in multiple crime categories in a single crime event, but they tend to persist with these same categories in future crime events. This observation may in part be due to different offenders undertaking different roles in some offending events – or at least being assessed as having undertaken such roles by police. Results reveal that actors tend to be involved in crime events that include familiar crime categories (i.e., those they have committed previously). This fits with existing knowledge on risk of reoffending – previous offending predicts future similar offending (e.g., Andrews, 1989; Hester, 2019;). For crime events involving co-offending, this familiarity effect is even stronger. This might indicate that group crimes are more often planned and are less spontaneous compared with individual crimes, and individuals tend to commit crimes with which they are familiar when engaging in co-offending.

We now focus on the results for heterophily and familiarity, and in particular the interaction of the two effects in the model. We use a simple example of three different co-offending partnerships to illustrate the combined influence of heterophily and familiarity. We use partnerships rather than larger groups in order to simplify the effects and draw conclusions that could then be applied to larger groups of co-offenders. The three hypothetical partnerships are composed as follows: group 1 (a1,a`1), group 2 (a2, a`2) and group 3 (a3, a`3). For each co-offending partnership, we predict the probability that each co-offending pair will engage in crime events involving only market crime. We consider the situation that at time *t*, actors a1, a`1, and a2 all have committed market crime previously while actors a`2, a3, and a`3 have not previously committed market crime.

For each of the three hypothetical co-offending partnerships, we calculated a group-based aggregate metric that represents the previous experience of the group in market crime (the 'familiarity effect'). For co-offending partnership 1, in which all actors have experience with market crime, this equals 1. For co-offending partnership 2, where half have experience with market crime, it equals 0.5. And for co-offending partnership 3, in which none of the group have experience with market crime, it equals 0. From the model, we calculated a 'previous experience' effect of 0.752 from which we can determine the magnitude of the increase in relative risk that each group of co-offenders will engage in market crime. For co-offending partnership 1, where all actors have experience in market crimes, the increase in relative risk is 112%. Group 2, where only one of the two co-offenders has engaged in market crime, has an increase in relative risk of 46%. And for group 3, where neither co-offender has experience in market crime, we find no increase in relative risk.

We then added the heterophily variable to the familiarity effect. In this example, we have three hypothetical co-offending partnerships: (1) Co-offending partnership 1, in which both co-offenders have the same previous experience with market crime / both have committed market crime (heterophily = 0); (2) Co-offending partnership 2, in which each co-offender has different previous experience with market crime. That is, one of them has committed market crime while the other has not (heterophily = 1); and (3) Co-offending partnership 3: both co-offenders have the same previous experience with market crime / neither have committed it (heterophily = 0). We calculated the net effect for heterophily in market crimes to be 2.225. Then, considering the combined effect of previous experience and heterophily, we find that these two effects multiply the risk that the co-offending partnerships engaged in market crime. For co-offending partnerships 1 and 3, the relative risk multiplies by 2.12 which is identical to the 'previous experience' effect while ignoring the heterophily effect. In contrast, for co-offending partnership 2, the relative risk increased to 13.48 and is much larger than when we ignore the heterophily effect.

In summary, the heterophily effect means that co-offending partnership 2, with mixed experience with market crime, are more likely to commit market crime in future. Thus, the potential effect of heterophily in market crimes shows that co-offending brings together experienced and inexperienced members and that this makes it more likely that the inexperienced member will commit the (new) offence in that co-offending partnership.

We now move to a discussion of heterophily and familiarity in property crime. For co-offending partnership 1, in which both co-offenders have previous experience with property crime, and co-offending partnership 2, in which one actor has experience with property crime and the other des not, each of these co-offending partnerships have about the same relative risk to engage in property crime. In contrast, co-offending partnership 3, where neither partner has experience with property crime, it is highly unlikely that they will commit property crime. The similar risk for co-offending partnerships 1 and 2 shows that there is an increased likelihood that a co-offender naïve to property offences will commit that offence when co-offending with an experienced accomplice compared with when they co-offend with an accomplice who shares this lack of experience.

Violent crime does not appear to follow the same pattern. The heterophily effect reveals that co-offending partnerships (and large co-offending groups) tend to show homogenous experience in violent crime. A group with mixed experience is highly unlikely to engage in violent crime. When violent crimes are committed by co-offenders, those co-offenders tend to have a history of engaging in violence. It appears unlikely that an individual without a history of violent offending will co-offend in violent crimes. This contrasts with the findings of one previous study that concluded there was contagion in violent offending (e.g., Conway and McCord, 2002). However, this previous study only examined the impact of the first co-offending event and examined a much younger cohort (aged 6–17 years at time of first offence). Further research is needed to unravel some of these co-offending dynamics with respect to violent offending. In our study, offenders without histories of market or property crime will engage in co-offending in those crimes, often with co-offenders who are experienced in undertaking such activities. The inexperienced offenders then have opportunities to learn skills and knowledge that facilitate such criminal activities, consistent with the predictions of social learning theories and differential association.

Finally, we posit some potential explanations for this pattern of results: Market crime is financially motivated, and usually involves more planning compared with other types of crime, including property crime and violent crime, which can be more spontaneous. In addition, as noted above, market crimes have more requirements for specific skills/knowledge (e.g., Bright et al., 2012, 2015) and need for key social contacts (e.g., Morselli, 2009). These elements can be contributed as part of the social learning and differential association that is fundamental to the social contact that can occur with experienced co-offenders. Put another way, market crimes arguably involve the need for both social and human capital, both of which can be enhanced via social contact and criminal collaboration with experienced offenders. Much property crime, such as robbery and theft, is also financially motivated and usually involves some planning although it can be spontaneous under some conditions. In addition, there is some need for skills/knowledge (e.g., breaking into cars, homes). There is therefore a need for human capital (i.e., skills and knowledge) that can be passed on to naïve offenders via contact and criminal experiences with co-offenders (see Akers and Jensen, 2011, 2017).

In summary, our results suggest that in the context of co-offending both market and property crime show evidence of differential association and social learning. Naïve partners in co-offending partnerships learn the skills and knowledge needed to participate in co-offending involving market and property crime. Co-offending in violent crime, on the other hand, may be more spontaneous, may be more related to individual proclivities compared to market and property crime. Violent crime appears less reliant on social learning of skills and shows less influence of differential association compared with market and property crime.

Implications

Results have several implications for scholarship and criminal justice policy and practice. First, results offer empirical support for theories of social learning in expanding criminal versatility, including co-offending as a potential driver of criminal versatility. Second, results confirm that studying co-offending is critical for understanding crime and for planning prevention and intervention strategies. Accurate estimations of the incidence of crime and its impact should include consideration of co-offending, especially given that co-offending tends to be associated with a broader range of crimes and potentially more serious social impacts. Third, co-offending offers opportunities for offenders to learn new types of crimes and expand one's repertoire of offending; police agencies should collect data on co-offending to help inform their understanding of crime patterns including solo crime and co-offending. This data collection and analysis should be conducted at a granular level (e.g., by specific crime type) to facilitate a clear picture of co-offending versus solo offending and to assist with the implementation of appropriate policing strategies. Finally, desistance efforts within prisons and in the community should take account of co-offending and the potential pro-criminal influences of co-offending partners (e.g., Halsey and Mizzi, 2023). For example, the social influence of co-offending partners could be positively engaged to motivate offenders to seek and attend rehabilitation programs. The social processes of mutual support and influence that can facilitate co-offending also offer opportunities for targeted policy interventions that include peer support and influence (this can be thought of as "rehabilitation through contagion").

Limitations

There are, of course, some limitations related to the data and analyses. First, as with all police data, the dataset only includes offences that were detected by police so the data underestimates criminal behaviour and co-offending. Second, the data includes only co-offenders who were arrested by the police. There could be co-offenders who were never arrested, and these people were not captured in the data. Further, offences classified as solo offences may indeed have involved co-offending, but the co-offenders remain undetected making the offending appear to be solo when it was co-offending. Third, arrests may reflect the focus of police investigations such that particular individuals are more likely to be arrested (see Bright, Brewer & Morselli., 2022 for a discussion of this and similar limitations in criminal networks research; also see Bouchard, 2020; Burcher and Whelan, 2018). Four, for the purposes of this project we operationalised co-offending as criminal collaboration (as most studies on co-offending do). However, although being arrested at the same crime event usually indicates criminal collaboration, it may also capture individuals arrested at a similar event who are not collaborating and may even be antagonists (e.g., a violent confrontation). It is indeed for this reason that we excluded 'public order offences'. In such offences, often large groups of individuals are arrested for participating in an offence such as protests or large riots. Finally, the motivation and intent of offenders cannot be identified based on the specific offences. For example, co-offenders engaged in organised retail theft schemes may be arrested for burglary and theft even though the crime would otherwise be categorised as a market crime.

Future research

Future research on co-offending networks should utilise RHEM as we argue these are the optimal analytical approach for co-offending and for data that incorporates events such as meetings (e.g., meetings of members of crime groups). In particular, more research is needed on co-offending across contexts and jurisdictions to examine the generalisability of our findings. Future research should also utilise different sets of crime categories to examine whether results hold using different approaches to categorising crime events. Research should also examine whether "intervention" efforts (i.e., policies and practices designed to prevent people from committing crimes) can also lead to social contagion; in this case, a form of desired social contagion.

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Appendix 1. Model results with age and sex included

Effects	Model 1	Model 2	Model 3
Incidents Involving Market Crimes	-2.588 (0.011) * **	-2.399 (0.011) * **	-2.368 (0.011) * **
Incidents Involving Property Crimes	-0.747 (0.005) * **	-0.689 (0.005) * **	-0.683 (0.005) * **
Incidents Involving Violent Crimes	-0.350 (0.005) * **	-0.299 (0.005) * **	-0.292 (0.005) * **
Incidents with multiple crime categories	-1.468 (0.030) * **	-1.479 (0.030) * **	-1.457 (0.030) * **
Number of crime categories of incidents	-1.062 (0.028) * **	-1.040 (0.028) * **	-1.074 (0.028) * **
Incidents involving Market and Property Crimes	0.631 (0.032) * **	0.470 (0.032) * **	0.521 (0.032) * **
Incidents involving Market and Violent Crimes	-0.811 (0.047) * **	-0.930 (0.047) * **	-0.906 (0.047) * **
Ratio of Females in Incidents involving Market Crimes	-0.177 (0.025) * **	-0.189 (0.026) * **	-0.176 (0.025) * **
Average Age in Incidents involving Market Crimes	0.050 (0.009) * **	0.045 (0.009) * **	0.038 (0.009) * **
Incidents involving Property and Violent Crimes	-0.008 (0.018)	-0.060 (0.018) * **	-0.036 (0.018) *
Ratio of Females in Incidents involving Property Crimes	0.240 (0.011) * **	0.207 (0.011) * **	0.207 (0.011) * **
Average Age in Incidents involving Property Crimes	-0.047 (0.004) * **	-0.035 (0.004) * **	-0.037 (0.004) * **
Ratio of Females in Incidents involving Violent Crimes	-0.245 (0.011) * **	-0.214 (0.011) * **	-0.213 (0.011) * **
Average Age in Incidents involving Violent Crimes	0.133 (0.004) * **	0.130 (0.004) * **	0.129 (0.004) * **
Group incidents with multiple crime categories	0.533 (0.067) * **	0.636 (0.067) * **	0.592 (0.067) * **
Number of crime categories of group incidents	0.928 (0.053) * **	0.706 (0.054) * **	0.953 (0.053) * **
Previous experience with crime categories		0.745 (0.005) * **	0.735 (0.005) * **
Heterophily in crime categories		-1.171 (0.052) * **	
Heterophily in market crimes		3.401 (0.115) * **	
Heterophily in property crimes		1.517 (0.056) * **	
Heterophily in violent crimes		0.872 (0.060) * **	
Group incidents previous experience with crime categories		1.116 (0.040) * **	0.781 (0.036) * **
Committing crimes of collaborators			0.226 (0.007) * **
AIC	954228.839	924222.541	924485.407
Num. events	332899	332899	332899
Num. obs.	4993485	4993485	4993485

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Note on robustness check.

We conducted a robustness check motivated by the assumption that the data may exclude (for a range of reasons) some participants of some crime incidents. To conduct the robustness checks, we randomly sampled 5% of the observed incidents. For each sampled incident we added a new participant, selected uniformly at random from all other actors. Thus, we increased the group size of the sampled incidents by one. We then fitted the same models to this distorted data. The robustness check analyses confirmed that the main conclusions remained stable.

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