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Spillovers in criminal networks: Evidence from co-offender deaths

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Spillovers in Criminal Networks: Evidence from Co-Offender Deaths*

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Abstract

We study spillover effects within criminal networks by leveraging the deaths of co-offenders as a source of causal identification. We find that the death of a co-offender significantly reduces the criminal activities of other network members. These spillover effects display a decaying pattern: offenders directly linked to a deceased co-offender experience the most significant impact, followed by those two steps away, and then those three steps away. Moreover, we find that the death of a more central co-offender leads to a larger reduction in aggregate crime, underlining the importance of network position in shaping spillover effects. We also provide evidence suggesting that the loss of a co-offender shrinks the future information set of offenders, which can influence their perceived probability of being convicted and consequently their criminal behavior. Our findings highlight the importance of accounting for spillover effects in designing more effective strategies for crime prevention.

Keywords: Networks, crime, peer effects, centrality measures, exogenous deaths, spillovers.
JEL classification codes: A14, D85, K42, Z13.

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1 Introduction

Empirical research highlights the important role of social interactions within networks in shaping criminal behavior (Lindquist & Zenou, 2019; Gavrilova & Puca, 2022). Social interactions give rise to significant spillover effects on behaviors that manifest in diverse forms and contexts. Understanding these spillovers is critical for designing effective strategies to prevent and mitigate crime. Despite their apparent importance, our empirical understanding of causal spillover effects generated within networks, and the role of network structure in shaping these effects, is incomplete. Key questions regarding the nature of the underlying mechanisms, and whether targeting central figures in criminal networks is effective in reducing crime, remain largely unanswered.

In this paper, we address these gaps by estimating the spillover effects of criminal behavior within co-offending networks, leveraging co-offender deaths as a natural experiment for causal identification.[1] These deaths serve as shocks to the network structure, enabling us to investigate whether and how offenders alter their criminal behavior when a co-offender is permanently removed from their network. We address three key research questions. First, does the death of a co-offender influence the criminal behavior of surviving network members? Second, does the magnitude of this effect depend on the centrality of the deceased co-offender within the network? In other words, can measures of network centrality predict which co-offenders have the greatest impact on crime upon their removal? Third, how does the loss of a co-offender affect the information available to surviving offenders about the likelihood of being convicted, and in turn, how does this change in information influence their criminal behavior?

To address these questions, we develop a network model in which offenders are connected when they commit a crime together. Two key aspects characterize this model. First, offenders generate positive spillover effects on their co-offenders by, for instance, sharing crime-related information or helping each other commit crimes more effectively. Second, offenders form beliefs about their probability of being convicted, relying on their own past experiences as well as those of their co-offenders.

We characterize the Nash equilibrium of this game and examine how the permanent removal of a co-offender from the network (due to death) impacts the criminal activities of offenders in the remaining network. Two effects are at play. First, when an offender dies, co-offenders experience reduced spillovers and consequently commit fewer crimes. The farther away in the network an offender is from the deceased, the smaller the crime-reducing spillover effect. The overall magnitude of this effect also depends on the network centrality of the deceased individual, with more central individuals exerting larger effects on aggregate crime reduction. Second, when someone dies, remaining offenders lose a source of future information regarding the probability of conviction if caught. If the death leads to an increase in the expected conviction rate, then surviving offenders may reduce their criminal efforts even further and commit even fewer crimes. On the other hand,

[1] Our identification strategy builds on a broader body of literature that employs deaths as an exogenous source of variation to study significant economic phenomena. See, for example, Jones & Olken (2005), Azoulay et al. (2010), Jaravel et al. (2018), Balsmeier et al. (2023), and Jäger & Heining (2024).

if the death leads to a decrease in the expected conviction rate, then two opposing effects operate: reduced spillover effects (lower crime), and lower expected conviction rate (increased crime). The net effect depends on the relative magnitudes of the spillover effect, the change in information, and the weight assigned to this change in information.

We test the predictions of our model using rich administrative data from Sweden spanning the years 2010 to 2012. The Swedish Suspects Register contains detailed information on all individuals suspected of committing a crime during this period, whether it is a solo-offense or a co-offense. For co-offenses, the register also includes information concerning individuals suspected of committing the crime together. Using this information, we construct an edge list of co-offenders involved in each crime for the period 2010 to 2012 and then transform it into a complete set of co-offending networks. In addition, we leverage data on convictions from the Swedish Convictions Register. Between 2010 and 2012, we observe 679 deaths among our sample of 108,018 co-offenders. We exclude 30 deaths due to assault, and use the remaining deaths as a source of conditionally exogenous variation in the structure of affected networks.

Our empirical analysis proceeds in three steps. First, we construct a monthly panel dataset at the individual offender level and estimate a robust dynamic difference-in-differences (DiD) model. We compare criminal behavior before and after the death of a co-offender, while controlling for individual and time fixed effects. We use both the never-treated and the not-yet-treated as our control groups. As such, our identification relies on the standard DiD parallel trends assumption. We confirm the absence of pre-trends in the data and then, in an alternative event study design that includes only offenders who at some point experience the death of a co-offender, we show that the exact timing of a co-offender death is conditionally exogenous to the criminal behavior of the surviving members of the network.

Our results indicate that the death of a co-offender significantly influences the criminal activity of other offenders within the same network, including total offenses, co-offenses, solo-offenses, the number of co-offenders, and convictions with or without a prison sentence. The estimated effect sizes are large and taper off as the network distance from the deceased co-offender increases. Total offenses for offenders who are directly linked to a deceased co-offender decrease by 47% of the pre-treatment mean, while those of offenders who are two-steps away decline by 15%, and those who are three-steps away by 8%. In terms of heterogeneity, the one-step-away effect for co-offenses (-94%) is much larger than the effect on solo-offenses (-31%), while the one-step-away effect on convictions with and without prison sentences is the same (-40%). Importantly, we also observe that deceased co-offenders are not being fully replaced by new co-offenders. All these findings are in line with our theoretical framework, which suggests that the permanent removal of a co-offender, such as through exit strategies and/or relocation policies, can have a lasting crime-reducing effect.

In the second step of our analysis, we shift our focus to the network level by aggregating the individual offender data. This approach yields a set of egocentric networks, each centered around a single deceased co-offender. These networks encompass all offenders who are one, two, or three steps removed from the deceased co-offender (the ego).

Our first network-level empirical exercise focuses on measuring the total spillover effects of a co-offender's death on the criminal activity of the surviving network members. This is done in a robust event study framework that includes only those networks that experience a co-offender death. We find that, on average, the death of a co-offender leads to an aggregate reduction in total (suspected) offenses of 13%. Spillover effects vary across outcomes, ranging from a 7% reduction in convictions with no prison sentence to an 18% decline in co-offenses. The number of co-offenders is reduced by 21%.

Our second network-level exercise investigates heterogeneity in these network-level spillover effects based on the eigenvector centrality of the deceased offender. Across all six outcomes, the death (and subsequent permanent removal) of a high-eigenvector-centrality offender leads to a significantly larger reduction in crime spillovers compared to the death of a low-eigenvector-centrality offender. This is true in both absolute terms and relative to the pre-treatment means of each group. Specifically, removing a high-eigenvector-centrality offender reduces total offenses by nearly 26% and the number of convictions involving prison sentences by 21%. These findings are in line with the predictions of our theoretical model.

Our third network-level exercise takes into account the number of crimes committed by the deceased offender by including these crimes in the network's pre-mortem total crime. This allows us to assess the overall reduction in crime that occurs after a co-offender's death, including both the deceased's own offenses and the spillover effects on other co-offenders. Moreover, we compare the effect of removing a high-eigenvector-centrality offender to the effect of removing an offender with a high offense rate. This comparison is particularly relevant for policy purposes, as police typically target individuals with high crime rates. The key question here is whether crime could be reduced even further by targeting offenders with a high eigenvector centrality, who generate large spillover effects within their network.

Our results demonstrate (once again) that the death of an offender with a high eigenvector centrality decreases aggregate network-level crime by substantially more than the death of a low centrality individual. Furthermore, the death of a high eigenvector centrality offender reduces crime by more than the death of a high offense rate co-offender, both in absolute and relative terms. This is an important result since it acts as a proof of concept for the idea that the police can use this simple measure of network centrality to target their efforts towards specific offenders, and in doing so reduce crime by more than the baseline policy of simply removing the most active criminal. In short, the police should target active players who are also highly central within their networks, since these offenders generate large spillover effects on their peers.

In the final section of our paper, we investigate additional predictions of our model related to changes in an offender's expectation of the probability of being convicted after losing a source of information within their network. We assign each individual a conviction probability, P, defined as the ratio of the number of convictions an offender has received to the number of times an offender has been suspected of a crime. A value of P equal to zero indicates that the offender is never convicted, while a value of P equal to one means that the offender is always convicted.[2] What happens when an offender loses a potential source of future information? On average, we find no effect. However, when the loss of an offender results in a large increase in the expected value of P, this leads to a small (but statistically significant) reduction in crime. Conversely, when the loss of an offender causes a large decrease in the expected value of P, we find a small (but statistically significant) increase in crime. These findings highlight the role of informational channels within co-offender networks that shape criminal activity by influencing perceived conviction risks.

Overall, our findings at both the individual and network levels underscore the critical role of spillover effects in shaping criminal behavior, offering valuable insights for policymakers aiming to design more effective crime-prevention strategies. Specifically, our results demonstrate that the permanent removal of a co-offender—whether through exit strategies or relocation policies—can yield lasting reductions in criminal activity. Moreover, our analysis provides a proof of concept for leveraging network centrality measures to identify key offenders who could be strategically targeted with focused deterrence initiatives. By prioritizing these individuals, policymakers can disrupt criminal networks more efficiently, amplifying the impact of intervention efforts.

Related Literature The economics of crime literature has produced substantial evidence demonstrating the importance of peer influence as a determinant of criminal and delinquent behavior.[3] The scope for peer influences may vary by crime type, as may the underlying mechanisms.[4] We make several original contributions to this literature. We provide causal estimates of the spillover effects of permanently removing a co-offender from their co-offending network by leveraging co-offender deaths for causal identification. Importantly, our analysis excludes the potential deterrence effects that may be present in studies measuring the spillover effects of arrests and incarceration. This approach allows us to more clearly identify a specific set of social mechanisms that operate within criminal networks.

We show that these spillover effects are both substantial and far-reaching, extending beyond direct peers (co-offenders). That is, we also find statistically significant and economically meaningful reductions in crime for individuals two and three steps away from the deceased co-offender. Furthermore, we find that these extended spillover effects decay as the network distance from the deceased co-offender increases. The spillover effects are evident across a wide array of crime types: co-offenses, solo-offenses, convictions with a prison sentence, and convictions without a prison sentence. In addition, our analysis indicates that co-offenders are not readily replaced; following the

[2] The average P across our full sample is 0.32, implying that, on average, offenders are convicted for approximately one-third of their suspected offenses.

[3] See Lindquist & Zenou (2019) and Gavrilova & Puca (2022) for reviews.

[4] Peers in this literature can be defined as friends (Patacchini & Zenou, 2012; Lee et al., 2021), family members (Hjalmarsson & Lindquist, 2012, 2013; Eriksson et al., 2016; Bhuller et al., 2018), neighbours (Glaeser et al., 1996; Ludwig et al., 2001; Kling et al., 2005; Damm & Dustmann, 2014; Bernasco et al., 2017; Dustmann & Landersø, 2021; Billings & Schnepel, 2022), schoolmates (Billings et al., 2014, 2019), people that serve time together in prison or juvenile jail (Bayer et al., 2009; Drago & Galbiati, 2012; Stevenson, 2017; Damm & Gorinas, 2020), homeless in shelters (Corno, 2017), co-workers in the military (Hjalmarsson & Lindquist, 2019; Murphy, 2019), and groups of co-offenders (Philippe, 2017; Bhuller et al., 2018; Domínguez, 2021; Craig et al., 2022).

loss of a co-offender, there is a permanent reduction in the number of unique individuals with whom surviving offenders co-offend in the future.

Our paper is also related to previous research that uses tools from social network analysis to design and evaluate focused deterrence strategies. Prominent examples include key player policies that provide strategies for choosing whom to focus police resources upon in order to achieve the largest reduction in crime (Ballester et al., 2006, 2010; Lee et al., 2021). These policies consider not only how much crime an individual commits, but also the amount of social influence the person has over others. Recent studies have evaluated key-player policies in various contexts,[5] while others have examined the importance of "central" agents in a network and their effect on different outcomes (Banerjee et al., 2013; Beaman et al., 2021; Mohnen, 2021; Zárate, 2023; Islam et al., 2024), showing that targeting the central (in terms of eigenvector or diffusion centrality) agents in a network increases diffusion.

Compared to this literature, we provide causal evidence that removing a more central offender results in a larger spillover effect than the removal of a less central offender. These reductions are also larger than those generated by removing the most active offender.[6] As such, we provide both causal evidence and a proof of concept of the potential efficacy of focused deterrence strategies, offender exit policies, and offender relocation polices. Importantly, our findings are based on data and methods that are easy to understand and readily available to the police, making them practical for real-world application.

Lastly, we also provide new insights into how perceptions of the likelihood of being caught, convicted, and punished—key components of the expected costs of committing a crime—affect criminal behavior (see e.g., Lochner (2007), Hjalmarsson (2009), and Philippe (2024)). Specifically, we exploit the fact that in our context of studying co-offender deaths, beliefs might shift due to the loss of a channel for gaining new information in the future. The deceased co-offender can no longer provide surviving offenders with new information, effectively shrinking the future information set by one source.

Outline In Section 2, we introduce a theoretical framework that illustrates how peer effects operate in co-offending networks. In Section 3, we describe our data creation procedures and provide descriptive statistics. In Section 4, we present our individual-level analysis, including the results. We present the results from our network-level analysis in Section 5. We then return to our individual-level analysis in Section 6, focusing on how offenders' behavior changes after receiving updated

[5] Lee et al. (2021) was among the first to propose a structural approach with network endogeneity to determine the key player. Other papers have examined the key firms that increase R&D spillovers (König et al., 2019), the key banks that reduce systemic risk (Denbee et al., 2021), the key "lockdown" areas in London that reduce the propagation of COVID-19 (Julliard et al., 2023), the key districts that increase growth in Africa (Amarasinghe et al., 2024), and the key districts that reduce total crime in England (Giulietti et al., 2024).

[6] Previous examples of the salience of such policies include the Boston Gun Project in 1995 and Operation Ceasefire in 1996, studied in the seminal works of (Braga et al., 2001) and (Kennedy et al., 2001). Operation Ceasefire placed extraordinary legal attention on a small number of gang members who were believed to be involved with (or connected to) a large share of the homicides in Boston. That is, the policy focused resources onto those whom the police believed to be the most active and/or relevant gang members.

information about the probability of conviction. We discuss the mechanisms of our results in Section 7, and conclude with a discussion of the policy relevance of our findings in Section 8.

2 Theoretical Framework

A co-offending network at time t, $\mathbf{g}_t$, is a collection of $N = \{1, 2, \ldots, n\}$ crime suspects and the links between them. The link between any two suspects is defined by $g_{ijt} \in \{0, 1\}$, where $g_{ijt} = 1$ when i and j are suspected of committing a crime together, i.e., they are co-offenders, and $g_{ijt} = 0$ otherwise. $\boldsymbol{G}_t = [g_{ijt}]$ is the corresponding adjacency matrix,[7] which describes the fixed architecture of the co-offender network at time t.

2.1 Model

Each agent chooses how many crimes to commit (their effort), $y_{it} \geq 0$, in order to maximize their own expected utility, $E[u_{it}(\boldsymbol{y}_t, \boldsymbol{G}_t)]$, which depends on (among other things) the crime profile of all agents in the network, $\boldsymbol{y}_t = (y_{1t}, ..., y_{nt})'$. Agent i's expected utility at time t is given by:

$$
\begin{aligned}
E[u_{it}(\boldsymbol{y}_t, \boldsymbol{G}_t)] = & \underbrace{(x_i + \epsilon_{it} + \eta_t)\, y_{it}}_{\text{proceeds}} - \underbrace{\frac{1}{2} y_{it}^2}_{\text{effort cost}} - \underbrace{E[p]_{it}\, E[f|p]_{it}\, y_{it}}_{\text{cost if caught and convicted}} \\
& + \underbrace{\phi \sum_{j=1}^{n} g_{ijt} y_{it} y_{jt},}_{\text{peer effects}}
\end{aligned}
\tag{1}
$$

where $\phi > 0$. Agent i's expected utility is a positive function of the proceeds from crime, $(x_i + \epsilon_{it} + \eta_t)\, y_{it}$, which are increasing in own effort, y_{it}, and where η_t and ϵ_{it} allow proceeds to vary across networks and individual offenders, respectively. Observe that x_i captures the *observable characteristics* of individual i, which do not vary over time, ϵ_{it}, represents the *unobservable characteristics* of individual i, and η_t is what is *specific to the network.* Involvement in crime also has an effort cost, an opportunity cost, and a social or moral cost. These costs, which are incurred with certainty, are captured by the quadratic loss term, $-\frac{1}{2}y_{it}^2$. Importantly, an agent's expected utility from crime is also increasing in the crime committed by their peers, y_{jt}. In our application, "peers" are defined as co-offenders who jointly commit crimes with the agent, i.e., $g_{ijt} = 1$. Peer effects are modeled as strategic complements such that $\phi > 0$. These spillover peer effects capture the positive effects that co-offenders exert on each other (for example, sharing information about crime opportunities or how to commit crime, etc.). $E[p]_{it}$ is the expected probability of being convicted for agent i at time t, while $E[f|p]_{it}$ is the expected punishment. In this section, we assume that criminals take $E[p]_{it}E[f|p]_{it}y_{it}$ as *exogenous.*[8] Thus, $E[p]_{it} = p_t$ and $E[f|p]_{it} = f$.

[7]Matrices and vectors are denoted in bold, while scalars are denoted in normal letters.

[8]We endogenize $E[p]_{it}$ in Section 6.1.

2.2 Equilibrium

Offenders simultaneously choose how many crimes to commit, $y_{it} \geq 0$, to maximize their own expected utility given by (1). Criminals take $\boldsymbol{y}_t$ and $\boldsymbol{G}_t$ as given when making this decision. The utility (1) can be written as:

$$E[u_{it}(\boldsymbol{y}_t, \boldsymbol{G}_t)] = (x_i + \epsilon_{it} + \eta_t)\, y_{it} - \frac{1}{2} y_{it}^2 - p_t\, f\, y_{it} + \phi \sum_{j=1}^{n} g_{ijt} y_{it} y_{jt}.$$

The best-reply function for each agent $i = \{1, \ldots, n\}$ is equal to

$$y_{it} = \phi \sum_{j=1}^{n} g_{ijt} y_{jt} + x_i + \eta_t + \epsilon_{it} - p_t f. \tag{2}$$

In matrix form, this can be written as:

$$\mathbf{y}_t = \phi \boldsymbol{G}_t \mathbf{y}_t + \mathbf{x} + \eta_t \mathbf{1} + \boldsymbol{\epsilon_t} - p_t f \mathbf{1},$$

where $\mathbf{1}$ is a vector of 1s. By solving this equation, we obtain:

$$\mathbf{y}_t = (\mathbf{I}_n - \phi \boldsymbol{G}_t)^{-1} \left[\mathbf{x} + \eta_t \mathbf{1} + \boldsymbol{\epsilon}_t - p_t f \mathbf{1}\right], \tag{3}$$

where $\mathbf{I}_n$ denotes the $n \times n$ identity matrix. Let $\mu_1(\boldsymbol{A})$ denote the largest eigenvalue (spectral radius) of the matrix $\boldsymbol{A}$. We have the following result:

Proposition 1. *If $\phi\mu_1(\boldsymbol{G}_t) < 1$, there is a unique Nash equilibrium of this game, given by (3). Moreover, if we denote by $x_{\min}$ the lowest value of vector $\mathbf{x}$, then if $x_{\min}$ is large enough, this equilibrium is interior.*

2.3 Nash equilibrium and eigenvector centrality

In the unique Nash equilibrium, criminal effort is proportional to a criminal's *eigenvector centrality*. To understand this result, let us provide a formal definition of eigenvector centrality.

Consider a network $\mathbf{g}_t$ with adjacency matrix $\boldsymbol{G}_t = [g_{ijt}]$. The eigenvector centrality $e_{it}(\boldsymbol{G}_t)$ of individual i at time t in network $\mathbf{g}_t$ is defined using the following recursive formula:

$$e_{it}(\boldsymbol{G}_t) = \frac{1}{\mu_1(\boldsymbol{G}_t)} \sum_{j=1}^{n} g_{ijt} e_{jt}(\boldsymbol{G}_t). \tag{4}$$

By the Perron-Frobenius theorem, using the largest eigenvalue guarantees that $e_{it}(\boldsymbol{G}_t)$ is strictly positive. In matrix form, we have:

$$\mu_1(\boldsymbol{G}_t)\mathbf{e}_t(\boldsymbol{G}_t) = \boldsymbol{G}_t \mathbf{e}_t(\boldsymbol{G}_t), \tag{5}$$

where $\mathbf{e}_t(\boldsymbol{G}_t)$ is the column vector of eigenvector centralities at time t. Eigenvector centrality assigns relative scores to all nodes in the network based on the principle that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes.

Proposition 2. *In the limit as $\phi \to 1/\mu_1(\boldsymbol{G}_t)$, the Katz-Bonacich centrality converges to eigenvector centrality, that is,*

$$\lim_{\phi \to \frac{1}{\mu_1(\boldsymbol{G}_t)}} (\mathbf{I} - \phi \boldsymbol{G}_t)^{-1} \mathbf{1} = \mathbf{e}_t(\boldsymbol{G}_t), \tag{6}$$

where $\mathbf{e}_t(\boldsymbol{G}_t)$ is defined by equation (5).

Proof of Proposition 2: The proof is standard. See, e.g., Newman (2010, Chap. 7), or Golub & Lever (2010). ∎

Proposition 2 implies that $\lim_{\phi \to \frac{1}{\mu_1(\boldsymbol{G}_t)}} y_{it} = e_{it}(\boldsymbol{G}_t)$, for each $i \in \mathcal{N}$, so that, in the limit as $\phi \to 1/\mu_1(\boldsymbol{G}_t)$, (3) can be written as:

$$y_{it} = \phi \sum_{j=1}^{n} g_{ijt} e_{jt}(\boldsymbol{G}_t) + x_i + \eta_t + \epsilon_{it} - p_t f. \tag{7}$$

Equation (7) demonstrates that an individual's criminal effort increases with the eigenvector centrality of their co-offenders. In other words, the more central and influential their co-offenders are within the network, the greater the individual's criminal effort tends to be.

2.4 Theoretical Predictions

To understand what happens to the remaining criminals in a network in terms of criminal behavior when a criminal k dies in the network, we examine the difference in criminal effort for individual i before and after the removal of criminal k:

$$y_{it}^{-[k]} - y_{it} = \underbrace{\phi \left(\sum_{j=1}^{n} g_{ijt}^{-[k]} y_{jt}^{-[k]} - \sum_{j=1}^{n} g_{ijt} y_{jt} \right)}_{\text{spillover effect}}.$$

In matrix form, this can be written as:

$$\mathbf{y}_t^{-[k]} - \mathbf{y}_t = \phi \left(\boldsymbol{G}_t^{-[k]} \mathbf{y}_t^{-[k]} - \boldsymbol{G}_t \mathbf{y}_t \right),$$

where the superscript $-[k]$ refers to the network when criminal k has been removed. In particular, the adjacency matrix $\boldsymbol{G}_t^{-[k]}$ is constructed by removing from $\boldsymbol{G}_t$ the row and column corresponding to k.

The key question is whether removing criminal k reduces the criminal effort of criminal i. When criminal k is removed, then $\sum_{j=1}^{n} g_{ijt}^{-[k]} y_{jt}^{-[k]} < \sum_{j=1}^{n} g_{ijt} y_{jt}$, because of strategic complementarities (Ballester et al., 2006). This is referred to as the *spillover effect*. We have the following result:

Proposition 3. *Assume $\phi \mu_1 (\boldsymbol{G}_t) < 1$. If criminal k is removed from the network, all other criminals reduce their effort. The farther a criminal is from k within the network, the less significant this reduction is. Conversely, the more central criminal k is (in terms of eigenvector centrality), the greater the reduction in criminal effort among their co-offenders.*

We now proceed to test these theoretical predictions empirically.

3 Data and Descriptive Statistics

We use the Suspects Register maintained by the Swedish National Council for Crime Prevention to compile a list of all individuals aged 15 or older who were suspected of committing a crime together at least once during the period from 2010 to 2012. Using this edge list, we construct a set of co-offending networks, resulting in a dataset of 29,369 networks and 108,018 individual offenders.

The size of these networks varies widely. The minimum network size is 2 offenders, the median network size is also 2, the mean network size is 4, and the maximum network size is 6,273. In addition, there are 438 networks that include 10 or more offenders, and 53 networks with 100 or more offenders.

For each offender, we calculate eigenvector centrality within their respective network. We classify them as a *highly central* offender if their centrality measure is above the median centrality measure within their own network. Similarly, we also classify offenders as *highly active* if the number of offenses they commit is higher than the median number of offenses within their own network.

3.1 Co-Offender Deaths

We match the offenders in our dataset to mortality information from Statistics Sweden's Full Population Register, using birth year and month of death (when applicable). In addition, we obtain data on the primary cause of death, from the National Board of Health and Welfare's Cause of Death Register, and hospitalization information from their Inpatient Register.

In our dataset of co-offenders, we observe 679 individuals who died between 2010 and 2012. Table 1 provides a breakdown of these deaths by main cause of death, along with additional information from the coroner indicating whether a death may be alcohol and/or narcotics-related. The most common cause of death is accidental, accounting for 255 deaths. Many of these accidents were either alcohol and/or narcotics-related, including car accidents or workplace accidents where the person was intoxicated, and accidental overdoses. Other leading causes of death include, events of undetermined intent, intentional self-harm, circulatory disease, and neoplasms (cancer). Nearly all deaths in this sample are premature, occurring before the individual turns 65, with a mean age at death of 40. In addition, most deaths are not preceded by long hospital stays; the mean number of nights spent in the hospital during the three months before the death month is only five.

We also investigate whether the criminal behavior of deceased individuals is trending up or down in the months preceding their death. For instance, if individuals who will die during the next year start to slow down or even stop committing crimes, then, in the presence of spillover effects (e.g., strategic complementarities), peers would actually begin being partially treated even before their co-offender passes away. This could muddy the interpretation of the timing of the treatment in our DiD and event study analyses. Alternatively, crime and conflict could be on the rise, which could affect the probability of dying (being murdered, for example) and simultaneously influence the future behavior of a deceased offender's peers (e.g., through retaliation).

To examine pre-mortem trends in crime, we focus on the 344 individuals who died in 2012. We can follow each of these offenders for at least 24 months prior to their death. In Figure 1, we see that the deceased individual's own crime does not display any trends in the months leading up to their deaths. Despite this lack of a trend in average pre-mortem crime, we exclude from our main analysis the 30 individuals who die from assaults in order to strengthen our argument that the exact timing of the death of a co-offender is conditionally exogenous with respect to the criminal behavior of their surviving peers.[9]

3.2 Individual-level monthly panel data

We match our sample of offenders to a set of individual-level characteristics to create an individual-level monthly panel dataset. From the Suspects Register, we track the number of unique solo-offenses and co-offenses that a person is suspected of each month. Solo-offenses and co-offenses are treated as separate outcome variables.[10] We also combine these offenses together when we examine total offenses as an outcome. By "unique", we mean the number of different crime types one is suspected of during the month. We also create a variable for the number of unique co-offenders that an individual is suspected of co-offending with each month. We further enrich our dataset by including monthly convictions and prison sentences as additional outcomes. These last two outcome variables are sourced from the Convictions Register, which is also maintained by the Swedish National Council for Crime Prevention.[11]

[9] Offenders enter our sample the first time they are suspected of a co-offense during the years 2010-2012. Our sample is fixed at the end of 2012 and includes all persons who are suspected of at least one co-offense during this period. New offenders enter each month so that the sample grows (linearly) over time. The number of deaths each month also grows (linearly) over time. An individual enters after his first co-offense and can then exit through death only after that co-offense occurs. Figure A1 in Appendix A, we show that the share of deaths each month is constant over time, where the share of deaths each months is calculated as the number of deaths in month T divided by the sum of all individuals that have entered the sample between $t = 1$ and $T - 1$. These are the offenders in our sample who could potentially die in month T.

[10] The 10 most common solo-offenses are: (1) narcotics use, (2) theft, (3) traffic, (4) assault, (5) threat, (6) narcotics possession, (7) fraud, (8) harassment, (9) driving under the influence, (10) domestic violence. The 10 most common co-offenses are: (1) fraud, (2) theft, (3) narcotics, (4) tax fraud, (5) assault, (6) property damage, (7) fraudulent bookkeeping, (8) narcotics possession, (9) narcotics selling and, (10) vehicular theft.

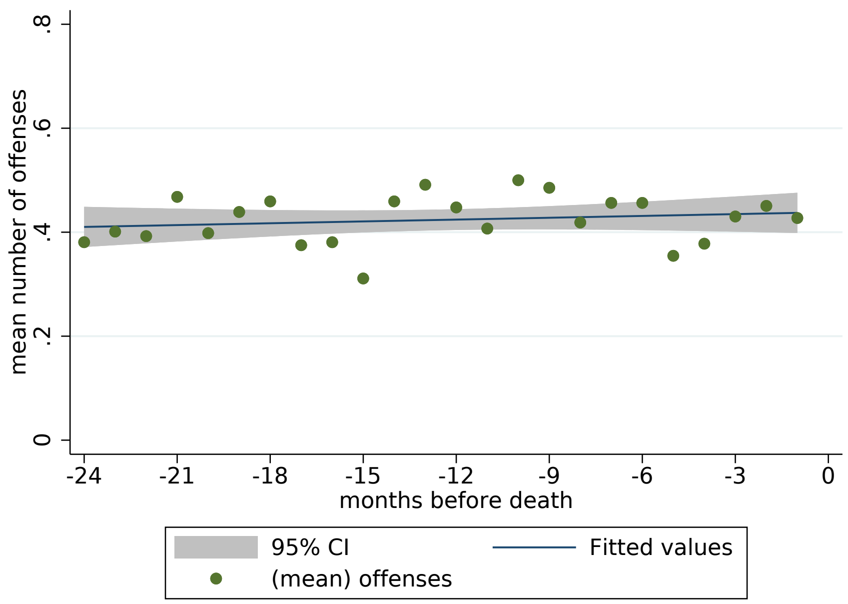
[11] An important detail to note here is that each outcome variable is assigned a date in time using the month in which the crime was committed and not the month in which the suspicion or conviction is officially registered, since in many

Table 1: Cause of Death, Age at Death, and Nights Spent in the Hospital

Cause of Death	N	Alcohol Related n	Narcotics Related n	Age at Death $Mean$	Nights in Hospital* $Mean$
Accidents	255	40	165	34	2
Assault	30	0	0	32	0
Blood, blood organs, certain immune m...	3	0	0	65	18
Certain infectous and parasitic disea...	12	0	2	45	19
Congenital malformations, deformation...	2	0	0	28	1
Diseases of the circulatory system	71	9	7	56	6
Diseases of the digestive system	30	18	5	55	12
Diseases of the nervous system	2	0	0	37	0
Diseases of the respiratory system	21	3	3	50	7
Endocrine, nutritional and metabolic...	6	0	2	33	0
Event of undetermined intent	77	14	50	34	3
Intentional self harm	74	3	8	30	2
Mental and behavioural disorders	17	8	10	49	5
Neoplasms	50	2	2	59	24
Other external causes	1	0	1	32	0
Symptoms, signs and abnormal clinical...	26	0	0	40	2
Unknown	2	0	0	35	0
Total/Subtotal/Subtotal/Mean/Mean	679	97	255	40	5

Notes: * Number of nights in the hospital during the three months preceding the month of death.

Figure 1: Average Number of Offenses in the Months Leading Up to Death



Notes: The sample used in this figure includes all offenders who die in 2012.

In our analysis, we exclude the 30 offenders who died from assaults during the sample period (2010-2012), as well as their co-offenders. We also drop the remaining 649 people who die during our sample period. Thus, only offenders who were still alive in December 2012 are included in our monthly panel data set. For each of these crime suspects, we go to their specific network and count the number of their co-offenders who died in any given month. We term this “co-offender deaths" or “one-step away deaths". We then count the number of co-co-offender deaths (two-step away deaths) and co-co-co-offender deaths (three-step away deaths).

Descriptive statistics for the individual-level panel dataset are shown in Table 2. On average, offenders in the sample commit a total of 6 (suspected) offenses during the 3-year period that we consider. About 2.2 of those are co-offenses and 3.8 are solo-offenses. In terms of convictions, they have on average 1 conviction not involving a prison sentence, and 0.17 convictions with a prison sentence. Panel B presents summary statistics on the number of unique 1-step, 2-step, and 3-step away co-offenders. On average, offenders have 2.5 co-offenders, 3.7 co-co-offenders, and 7.9 co-co-co-offenders. Panel C of the table also reports the occurrence of co-offender deaths. We see that about 1.15% of the sample experiences one 1-step away death and that very few experience more than one such death. The incidence of at least one two-step away death is slightly higher at 2.14%, while that of a three-step away death is even higher at 4.03%.

Table 2: Descriptive Statistics for Individual-Level Data

	mean	sd	min	p50	max
A. Outcomes					
Total Offenses	5.989	9.457	1	2	177
Co-Offenses	2.171	2.709	0	1	75
Solo-Offenses	3.818	8.017	0	1	156
Total Co-offenders	3.184	7.726	0	2	999
Convictions No Prison	0.994	1.542	0	0	20
Convictions Prison	0.169	0.559	0	0	9
B. Network characteristics					
Unique co-offenders	2.5	3.3	0	1	83
Co-co-offenders	3.7	8.9	0	0	158
Co-co-co-offenders	7.9	24.2	0	0	468
C. Deaths					
Count of Deaths	0	1	2	3	> 3
1-Step	105,993	1,234	33	4	-
2-Step	104,905	2,012	227	49	8
3-Step	102,739	3,193	646	193	279

Notes: Sample includes 107,264 offenders. Reported outcomes in panel A refer to sums over the 36-months spanning our sample. Panel B provides summary statistics on the number of unique 1-step, 2-step, and 3-step away co-offenders. Panel C presents summary statistics on number of deaths experienced by offenders in the sample.

cases this registration occurs at a later date, especially for convictions.

3.3 Network-level monthly panel data

We also create a network-level monthly panel dataset, by re-arranging the monthly offender-level panel dataset. Specifically, for each of the 649 co-offenders who died from causes other than assault during the 2010-2012 period, we build an egocentric network around them. We match each of the 649 individuals to their co-offenders (i.e., those who are only one-step away), their co-co-offenders (two-steps away), and co-co-co-offenders (three-steps away). We then collapse (by summing) these data into aggregate, egocentric network-level data. This results in a monthly panel of aggregate crime outcomes for all individuals belonging to each egocentric network. When constructing these egocentric networks, we exclude three pairs of deceased offenders due to network overlap, which leaves us with 643 egocentric networks, each with only one deceased offender.

Descriptive statistics for the network-level data are shown in Table 3. The minimum network size is 2 offenders, the median size is 6 offenders, and the largest network includes 328 offenders. On average, these networks commit 100 co-offenses and 321 solo offenses. They also receive nearly 63 convictions without a prison sentence and 16 convictions that include a prison sentence. Furthermore, 27% of networks experience the death of a high eigenvector centrality offender, while 70% experience the death of an offender with a relatively high number of offenses.

Table 3: Descriptive Statistics for Aggregate-Level Network Data

	count	mean	sd	min	p50	max
Network Size	643	17.79	32.18	2	6	328
Offenses	643	421.50	1051.04	2	75	11082
Co-Offenses	643	100.47	248.47	1	15	2597
Solo-Offenses	643	321.03	805.67	0	55	8485
Conviction No Prison	643	62.51	153.59	0	12	1588
Conviction Prison	643	15.67	39.74	0	2	434
High Eigenvector Centrality	643	0.27	0.45	0	0	1
High Offender	643	0.70	0.46	0	1	1
Death Time	643	23.59	8.80	2	25	36

4 Individual-Level Spillover Analysis

4.1 Empirical strategy

To estimate individual-level spillover effects, we leverage co-offender deaths as a source of exogenous variation. Specifically, we study the extent to which the permanent removal of a former co-offender affects the future criminal behavior of the surviving offenders. We do this in a difference-in-differences (DiD) framework.

The treatment for offender i is defined as the death of their co-offender k at time t. Furthermore, we distinguish between co-offender deaths that are one, two, and three links l away from each offender. Our theoretical framework predicts that spillover effects should taper off as l increases.

We estimate a dynamic DiD model using the Borusyak et al. (2024) two-step imputation method, which is robust to both heterogeneous and time-varying treatment effects. This approach addresses concerns raised in recent literature regarding the validity of DiD designs with variation in treatment timing under treatment effect heterogeneity (de Chaisemartin & D'Haultfoeuille, 2023; Roth et al., 2023). For each link distance $l \in \{1, 2, 3\}$, we estimate the following specification:

$$Y_{it} = \alpha_i + \beta_t + \sum_{j=-12}^{12} \tau_j \mathbf{1}[\text{time since death} = j] + \epsilon_{it}, \tag{8}$$

where Y_{it} represents the outcome of offender i at calendar time t; α_i and β_t denote offender-by-death and year-by-month fixed effects, respectively.[12] $\mathbf{1}[\text{time since death} = j]$ are indicator variables that track the number of months since the death of a co offender has occurred; $j = t - E_i$, where E_i is the month when i experiences the death of a co-offender.

When $j \geq 0$, the coefficients τ_j trace out the dynamic treatment effects. Estimates of τ_j when ($j < 0$) allow us to test for parallel pre-trends and anticipation effects. We include 12 leads and lags to construct a symmetric two-year window centered around the event. We estimate (and test) pre-trends separately from our dynamic treatment effects and we cluster standard errors at the offender i level.

To obtain a summary of the average treatment effect during the entire 12-month post-event period, we also estimate a static DiD specification:

$$Y_{it} = \alpha_i + \beta_t + \tau D_{it} + \epsilon_{it}, \tag{9}$$

where D_{it} is an indicator variable that takes the value one when individual i experiences the death of a co-offender and remains at one for all subsequent time periods. In this specification, the parameter τ captures the static treatment effect of a death of a co-offender on criminal outcomes Y_{it} net of unit and time fixed effects. Standard errors are clustered at the offender i level.

Identifying assumptions The main identifying assumption embedded in the standard DiD framework is the parallel post-treatment trends assumption: in the absence of treatment, outcomes of the treatment and comparison groups would have evolved along the same path in the post-treatment period. This assumption allows us to claim that the never-treated group does, in fact, act as a valid counterfactual for the treated group, after netting out individual or group fixed effects.

In our dynamic setting, in which treatment can occur in any of the months (except in the first), the not-yet-treated group also acts as a control for the treated. The assumption needed for this group to function as a valid control group is that the timing of the treatment (the death of co-offender k) is

[12] As some offenders experience multiple deaths of co-offenders, the unit in our panel data set is defined by unique offender-by-death events. Hence, the unit fixed effects in equation (8) are set at that level. In section 4.3, we reestimate spillover effects for those who experience only one unique death.

conditionally exogenous to offender i's criminal behavior, after conditioning on individual and time fixed effects. If this holds, then those just treated will be similar in both observable and unobservable characteristics to those who will be treated in the next period. If treatment is conditionally randomly assigned in every period then the treated and comparison groups should be balanced over time and, hence, fulfill the assumption of parallel post-treatment trends.

Borusyak et al. (2024)'s two-step imputation method estimates individual and time fixed effects using data from those who are never-treated and those who are not-yet-treated. Then each individual is assigned his or her own counterfactual value, $\hat{Y}_{0,it} = \hat{\alpha}_i + \hat{\beta}_t$, and treatment effect, $\hat{\tau}_{it} = Y_{it} - \hat{Y}_{0,it}$. The parallel trends assumption is embodied in $\hat{\beta}_t$. Our estimate of $\hat{\tau}_j$ is simply the average value of all $\hat{\tau}_{it}$s.

If we assume that $\hat{Y}_{0,it} = \hat{\alpha}_i + \hat{\beta}_t$ is a correct specification of the true counterfactual, then we are implicitly assuming away unobserved shocks, u_{i0}, that could (at least in theory) both cause an event and affect future outcomes. We are also assuming away time-varying (unobservable) individual effects, γ_{it}. Thus, we may want to have a richer, alternative model of the unobserved counterfactual in mind when thinking about threats to identification, e.g., $Y_{0,it} = \alpha_i + \beta_t + \gamma_{it} + u_{i0}$.

Addressing potential threats to identification There exist several potential threats to identification of unbiased treatment effects. First, the parallel post-treatment trends assumption may not hold. While this is a fundamentally untestable assumption, we do provide a close inspection and test of all pre-treatment trends and show that there are no pre-trends in our empirical exercises (see Figures 2, 3, and 4 below). We also look for anticipation effects in these figures, i.e., changes in the behavior of those who will soon be treated, and find no such effects. These observations strengthen our belief in the validity of the post-treatment parallel trends assumption.

In Figure A2, we also show results from a pure event study that drops all never-treated individuals from the control group. We see no indications of anticipation effects or non-parallel trends in these event study exercises. Thus, the exact timing of co-offender deaths appears to be conditionally exogenous with respect to the outcomes of surviving co-offenders.

Second, one might also worry that those who are ill and will die in the near future might stop committing crimes before they die. This would mean that the remaining offenders have already begun receiving the treatment of being exposed to less criminal behavior from their peers before the actual date of the event. However, Figure 1 suggests that the criminal behavior of those who will die does not trend up or down before their deaths. Furthermore, Table 1 confirms that very few of those who will die spend any significant amount of time in the hospital in the months preceding their deaths. Lastly, as mentioned above, we see no signs of behavioral changes among offenders in the time leading up to their co-offender's death.

We also want to safeguard against specific shocks (the u_{i0} mentioned above) that both cause the co-offender death and affect the crime of surviving offenders. An example of this would be a conflict that we cannot observe that leads to the murder of a co-offender, which in turn could encourage retaliation from surviving co-offenders. Alternatively, offender i could stage a hostile takeover of his own criminal network by killing co-offender k, thereby increasing offender i's future crime. Both examples illustrate how unobserved shocks can cause both the death and changes in criminal behavior and, hence, lead to spurious estimates of the spillover effects that we aim to identify. It is this concern that motivated us to exclude deaths due to assaults from our baseline analysis.

More generally, the DiD estimation strategy assumes the absence of unobserved shocks, u_{i0}, that cause the event or treatment and affect subsequent behavior and time-varying individual level unobservables, γ_{it}. Our identification strategy, however, combines the standard DiD estimation framework together with the identification strategy used in the exogenous death literature. In our setting, we have reasons to believe that our event is randomly assigned across time periods. For example, Figure A1 shows that the share who die is spread evenly across all months. As such, the variation that we use to estimate spillover effects should be orthogonal to both time-varying unobservables of the surviving offenders and to unobserved shocks. This works to strengthen our causal identification strategy in a way that other DiD strategies may lack.

Finally, robustness checks provide further support to our findings. We show that our main results are robust to using smaller samples and more strict definitions of death that are sudden, unexpected, accidental, or particular medical conditions; such that the exact month of death of an offender cannot be reasonably predicted by his surviving co-offenders.

4.2 Results

Figures 2, 3, and 4 illustrate the dynamic effects of one-step, two-step, and three-step away deaths on the crime outcomes of surviving co-offenders. Table 4 presents static DiD estimates of the overall impact of co-offender deaths in the post-treatment period, along with pre-treatment means of each outcome and p-values from testing the null of no pre-trends.

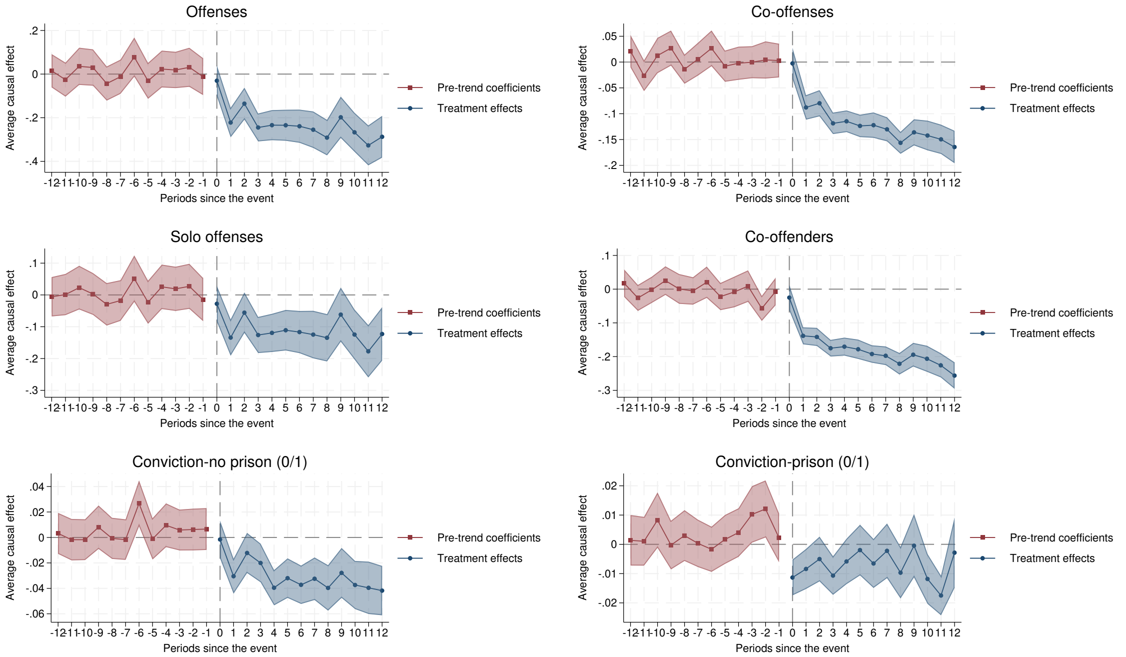
One-step away deaths. In Figure 2, we observe no meaningful pre-trends for any of the outcomes and the p-values for tests of the null of no pre-tends are well above 0.10 (see Table 4a). The death of a co-offender leads to statistically significant and economically meaningful reductions in all crime outcomes. These effects are persistent and, in some cases, grow over time.

Total suspected offenses are reduced by -0.28 offenses, which corresponds to a -48% reduction relative to the pre-treatment mean of 0.58. Suspected co-offenses drop by -94%, while suspected solo-offenses are reduced by -31%. The number of unique co-offenders is reduced by -0.21 (-116%), which implies that the deceased co-offender is not being fully replaced. Crimes that lead to future convictions (both with and without prison sentences) are reduced by -40% due to the permanent removal of a one-step away co-offender.[13]

Two-step away deaths. Figure 3 illustrates the dynamic effects of experiencing the death of a co-co-offender. Static DiD effects are reported in Table 4b. While, the qualitative pattern of these effects

[13]Recall that we date our outcome variables by the month that the crime was committed and not by the month that the suspicion or conviction was officially registered.

Figure 2: Impact of one-step away deaths.



Notes: The figures plot estimates of the dynamic DiD model in equation 8 for one-step away deaths estimated using the Borusyak et al. (2024) two-step imputation method. 5% confidence intervals are shown, using standard errors clustered at the offender i level.

are similar to those generated by one-step away deaths, effect sizes from two-step away deaths are much smaller. For total suspected offenses we estimate a decrease of -0.10 offenses, which amounts to a -15% reduction relative to the pre-treatment mean (0.68). The largest decrease is observed in the number of unique co-offenders (-28%), while the smallest is in convictions without prison sentences (-11%).

Three-step away deaths. Figure 4 illustrates the dynamic effects of experiencing the death of a co-co-co-offender, with static DiD effects reported in Table 4c. While, the qualitative pattern of these effects are fairly similar to those generated by one- and two-step away deaths, effect sizes from three-step away deaths are quite small, and in the case of convictions with no prison sentences statistically insignificant. Total suspected offenses are reduced by -0.06 offenses, which is a reduction of about -8% relative to the pre-treatment mean (0.75). Similarly small reductions are seen for both solo- and co-offenses, while the number of co-offenders is reduced by -0.03 (-12%).

Summary Overall, these findings highlight the large spillover effects that the death of an offender can have on the crime activity of other offenders in their co-offending network. Notably, these effects extend beyond their direct co-offenders, impacting individuals who are not directly linked to the deceased offender. Furthermore, our findings suggest a decaying pattern in the magnitude of these

Table 4: The Impact of Co-offender Deaths on the Crime Outcomes of Former Peers

(a) One-Step away deaths

	(1) Offenses	(2) Co-Offenses	(3) Solo-Offenses	(4) Co-Offenders	(5) Conviction No prison	(6) Conviction Prison
DiD	-0.277***	-0.140***	-0.137***	-0.217***	-0.035***	-0.009***
	(0.023)	(0.009)	(0.019)	(0.012)	(0.005)	(0.002)
Observations	3,863,088	3,863,088	3,863,088	3,863,088	3,863,088	3,863,088
number of clusters	107,264	107,264	107,264	107,264	107,264	107,264
p-value no pre-trends	0.336	0.382	0.628	0.179	0.436	0.358
pre-treatment mean	0.585	0.149	0.436	0.187	0.087	0.022

(b) Two-Step away deaths

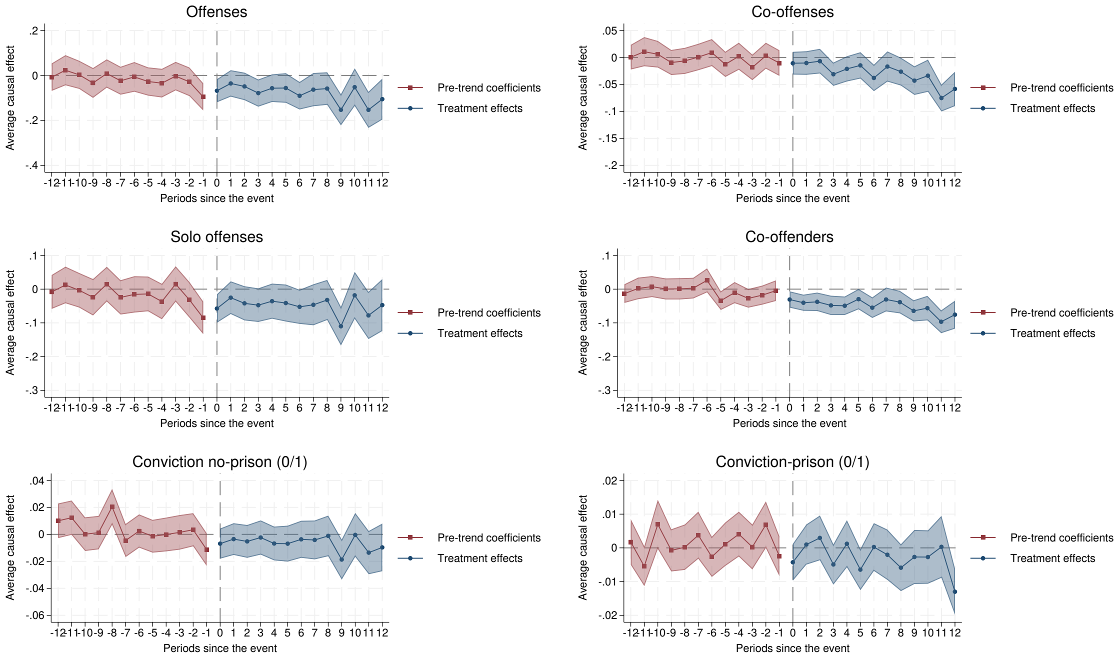
	(1) Offenses	(2) Co-Offenses	(3) Solo-Offenses	(4) Co-Offenders	(5) Conviction No prison	(6) Conviction Prison
DiD	-0.100***	-0.034***	-0.066***	-0.057***	-0.011***	-0.003*
	(0.020)	(0.007)	(0.016)	(0.009)	(0.003)	(0.001)
Observations	3,872,844	3,872,844	3,872,844	3,872,844	3,872,844	3,872,844
number of clusters	107,201	107,201	107,201	107,201	107,201	107,201
p-value no pre-trends	0.215	0.750	0.047	0.141	0.032	0.199
pre-treatment mean	0.684	0.164	0.520	0.203	0.099	0.025

(c) Three-Step away deaths

	(1) Offenses	(2) Co-Offenses	(3) Solo-Offenses	(4) Co-Offenders	(5) Conviction No prison	(6) Conviction Prison
DiD	-0.059***	-0.012**	-0.047***	-0.028***	-0.003	-0.003***
	(0.018)	(0.006)	(0.014)	(0.007)	(0.003)	(0.001)
Observations	3,943,692	3,943,692	3,943,692	3,943,692	3,943,692	3,943,692
number of clusters	107,050	107,050	107,050	107,050	107,050	107,050
p-value no pre-trends	0.120	0.297	0.358	0.388	0.037	0.982
pre-treatment mean	0.747	0.181	0.566	0.232	0.110	0.028

Notes: This table report static DiD coefficients estimated with Borusyak et al. (2024)'s two-step imputation method. Standard errors (in parentheses) are clustered at the individual level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 3: Impact of two-step away deaths.



Notes: The figures plot estimates of the dynamic DiD model in equation 8 for two-step away deaths estimated using the Borusyak et al. (2024) two-step imputation method. 5% confidence intervals are shown, using standard errors clustered at the offender i level.

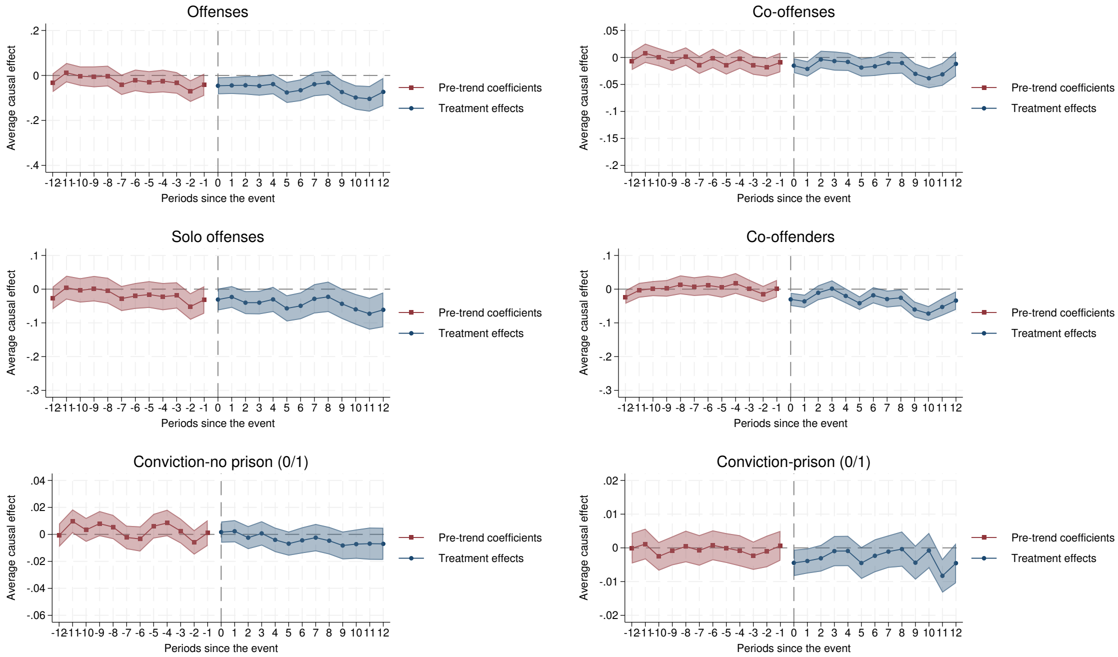
spillover effects, with individuals directly linked to a deceased offender experiencing the greatest impact, followed by those who are two steps away, and finally those who are three steps away. These empirical findings are in line with the predictions of our theoretical model, as summarized in Proposition 3 in Section 2.

Robustness and placebo tests In our sample period, some offenders experience more than one death. This raises the possibility that the effects estimated in the previous section may be partially influenced by these multiple treatments that occur at various distances. To isolate the treatment effect of unique, single-death events, we re-estimate our empirical model using the subset of offenders who have experienced only one death during this time period. This single-death event can occur at either one, two, or three steps away.

Table A1a in Appendix A presents results for unique deaths occurring one step away. As before, the death of a one-step-away co-offender significantly reduces all crime outcomes. While the estimated coefficients are slightly smaller than those shown in Table 4a, so are the pre-treatment means. This implies slightly larger treatment effect sizes. For example, the effect size on total suspected offenses increases from 48% to 56%.

We also see a more rapid fade-out pattern in Table A1 when compared to Table 4. Unique, three-step-away deaths have little (if any) effect on solo-offenses, co-offenses, and lesser convictions that

Figure 4: Impact of three-step away deaths.



Notes: The figures plot estimates of the dynamic DiD model in equation (8) for three-step away deaths estimated using the Borusyak et al. (2024) two-step imputation method. 5% confidence intervals are shown, using standard errors clustered at the offender i level.

include no prison sentence.

In Appendix Table A2, we report various additional robustness checks. We show that our baseline findings reported in Table 4 are robust to (i) excluding causes of death related to alcohol and narcotics (Panel A), (ii) restricting attention to deaths occurring between the ages of 18 and 65 (Panel B), (iii) restricting attention to deaths caused by accidents unrelated to alcohol or narcotics (Panel C), (iv) excluding deaths that are preceded by long hospitalization periods (more than 5 days) in the months immediately preceding the death (Panel C). For brevity, we report these robustness checks for one-step-away deaths.

To provide further support for our findings, we conduct a placebo test. We randomly reshuffle the events (death of a one-step-away co-offender) across offenders in our sample, while maintaining the total number and timing distribution of the events constant. We then estimate 100 iterations of the static difference-in-differences specification (equation (9)) and obtain a set of placebo estimates that we compare with our baseline estimates for each of the 6 outcomes reported in Table 4a. In Table A3, we find that this exercise produces a set of precisely estimated zeros, with no iteration produced a larger estimate than our baseline estimates. This provides further reassurance that our estimates are uncovering true spillover effects.

5 Network-Level Analysis

Proposition 3 posits that the more central an offender was before their death (in terms of eigenvector centrality), the greater the reduction in criminal effort among their former co-offenders after their death. In our model, the removal of an offender with a high eigenvector centrality measure generates larger spillover effects than the removal of a less central individual, all else equal. We now test this prediction using our network-level monthly panel data described in Section 3.3.

5.1 Empirical Strategy

Our network-level centrality analysis is carried out using a similar two-way fixed effects specification as in our individual-level analyses above, albeit with some key differences. First, we focus only on networks that actually experience the death of a co-offender. Thus, we are estimating a DiD event study design rather than a DiD design that includes a never-treated control group. Second, the crime data are now aggregated (summed) up to the network level. We therefore replace the individual-level subscript, i, with the network-level subscript, n. Third, we want to compare networks that are roughly similar in terms of size, and therefore control for bins of network size, s.

Importantly, when estimating the effects of network centrality on the total spillover effect that arises from removing a specific offender i, we exclude the crime of the deceased co-offender from both the pre- and the post-death periods. We estimate the following equation:

$$Y_{n[-i]ts} = \alpha_{n[-i]} + \beta_t + \gamma_s + \tau D_{n[-i]ts} + \epsilon_{n[-i]ts}, \tag{10}$$

where $D_{n[-i]t}$ is an indicator variable that turns from zero to one at the co-offender death date, and remains at one for all subsequent periods; $\alpha_{n[-i]}$, β_t, and γ_s are network, month-by-year, and network size bin fixed effects, respectively. The parameter τ captures the average treatment effect of a death of a co-offender on the crime outcomes ($Y_{n[-i]t}$) of the surviving network members, net of network- and time-specific effects (i.e., the network-level spillover effects).

As before, we estimate τ using the Borusyak et al. (2024) robust imputation method. We cluster standard errors at the network level. This two-step imputation method produces an estimate of τ for each network, $\hat{\tau}_n$. This, in turn, allows us to produce separate estimates of the treatment effect associated with the death of a high versus low eigenvector centrality co-offender.

5.2 Results: The Effect of Eigenvector Centrality on Crime-Reducing Spillovers

In Table 5, we present estimates of the average network-level spillover effects that arises after the death of a co-offender for each of our six outcome variables. We also investigate how the centrality of the deceased offender affects the size of these spillover effects.

Average treatment effects are shown in columns (1), (3), and (5) of Table 5. For total offenses, the death of a co-offender results in a statistically significant reduction of -1.62 offenses. This amounts to a 13% reduction relative to the pre-treatment mean of 12.37 total suspected offenses. Spillover effects on crime range from -7% for convictions with no prison sentence to -18% for co-offenses. The number of co-offenders declines by 21%. Note also that we report the p-value from our pre-trends test for each DiD event study regression, with most p-values exceeding 0.10, indicating no significant divergence in trends prior to treatment.

Our centrality exercise tests for heterogeneous effects. These are shown in columns (2), (4), and (6) of Table 5. For each of our six outcomes the death of a high eigenvector centrality offender leads to a significantly higher reduction in crime spillovers compared to the death of a low eigenvector centrality offender. This is true in both absolute terms and relative to the pre-treatment means of each group. Removing a high eigenvector centrality offender generates spillover effects that reduce total offenses by nearly 26% and the number of convictions that include prison sentences by 21%. These empirical results support the predictions of our theoretical model outlined in Proposition 3.

5.3 Results: The Effect of Network Centrality on Total Crime Reduction

In this section, we measure the total reduction in crime that occurs after a co-offending network experiences the death of one of its members. To do this, we repeat the exercise from the previous section, but now also include the pre-mortem crimes committed by the deceased co-offender. We want to sum up the spillover effect (as measured above) together with the reduction due to the deceased offender's *own* crime going to zero.

In addition, we compare the effect of removing a high eigenvector centrality offender to that of removing a person with a high offense rate. This is a particularly relevant comparison from a policy perspective: police do not typically focus on people at random, but rather focus their attention on people who commit more crimes. The question here is whether or not they could reduce crime even further by targeting offenders with a high eigenvector centrality who generate large spillover effects.

In column (1) of Table 6, we see that the average effect on total (suspected) offenses is a reduction of 2.04 crimes, which is approximately 16% of the pre-treatment mean. Co-offenses drop by as much as 20%, while convictions without a prison sentence drop by 10%.

Importantly, we cannot reject that the average number of co-offenders drops by exactly one person, which implies that (in contrast to popular belief) old co-offenders are not being immediately replaced by new co-offenders. In our model, this permanent reduction in the number of co-offenders implies a permanent reduction in crime spillovers and aggregate network-level crime.

In colums (2), (5), and (8) of Table 6, we see that the death of an offender with a high eigenvector centrality decreases aggregate network-level crime by substantially more than the death of a low centrality individual. Furthermore, the death of a high centrality offender reduces crime by more than the death of a high offense rate co-offender; both in relative and absolute terms.[14] This is also an important finding since it acts as a proof of concept for the idea that the police can use this simple measure of network centrality to target their efforts towards specific offenders, and in doing so reduce crime by more than the baseline police of simply removing the most active criminal.

[14] Compare columns (2), (5), and (8) of Table 6 to columns (3), (6), and (9).

Table 5: Network Level Spillover Effects: High vs. Low Eigenvector Centrality

Panel A	(1) Total offenses	(2) Total offenses	(3) Solo offenses	(4) Solo offenses	(5) Co-offenses	(6) Co-offenses
Average effect	-1.622***		-1.091***		-0.531***	
	(0.336)		(0.262)		(0.0900)	
Low eigenvector centrality		-0.855***		-0.498**		-0.356***
		(0.315)		(0.232)		(0.0973)
High eigenvector centrality		-3.715***		-2.707***		-1.008***
		(0.841)		(0.691)		(0.184)
p-value no pre-trends	0.55	0.55	0.31	0.33	0.84	0.87
pre-treatment mean	12.37		9.36		3.00	
p-value for equality		0.00		0.00		0.00
pre-treatment-low mean		11.54		8.81		2.73
pre-treatment-high mean		14.54		10.81		3.73
Panel B	Co-offenders	Co-offenders	Convictions no prison	Convictions no prison	Convictions prison	Convictions prison
Average effect	-0.807***		-0.122***		-0.0612***	
	(0.132)		(0.0418)		(0.0160)	
Low eigenvector centrality		-0.457***		-0.0267		-0.0414**
		(0.123)		(0.0443)		(0.0162)
High eigenvector centrality		-1.762***		-0.381***		-0.115***
		(0.313)		(0.0935)		(0.0368)
p-value no pre-trends	0.94	0.94	0.08	0.08	0.98	0.98
pre-treatment mean	3.81		1.81		0.46	
p-value for equality		0.00		0.00		0.07
pre-treatment-low mean		3.21		1.71		0.43
pre-treatment-high mean		5.37		2.09		0.54
Observations	23,148	23,148	23,148	23,148	23,148	23,148
number of clusters	643	643	643	643	643	643

Notes: This table reports event study estimates using the Borusyak et al. (2024) two-step imputation method. Standard errors (in parentheses) are clustered at the network level: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 6: Network Level Reduction in Total Crime

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Eigenvector centrality	Offense rate		Eigenvector centrality	Offense rate		Eigenvector centrality	Offense rate
Panel A	Total offenses	Total offenses	Total offenses	Solo offenses	Solo offenses	Solo offenses	Co-offenses	Co-offenses	C0-offenses
Average effect	-2.038***			-1.414***			-0.623***		
	(0.340)			(0.267)			(0.0901)		
Low		-1.223***	-1.075**		-0.786***	-0.607		-0.438***	-0.468***
		(0.321)	(0.546)		(0.237)	(0.388)		(0.0973)	(0.172)
High		-4.259***	-2.361***		-3.129***	-1.685***		-1.130***	-0.676***
		(0.848)	(0.406)		(0.698)	(0.325)		(0.184)	(0.101)
Pre-treatment mean	12.81			9.712			3.099		
p-value for equality		0.00	0.06		0.00	0.03		0.00	0.29
Pre-treatment mean low		11.92	5.95		9.11	4.47		2.81	1.489
Pre-treatment mean high		15.15	16.08		11.29	12.21		3.85	3.87
Panel B	Co-offenders	Co-offenders	Co-offenders	Convictions no prison	Convictions no prison	Convictions no prison	Convictions prison	Convictions prison	Convictions prison
Average effect	-0.914***			-0.182***			-0.0727***		
	(0.133)			(0.0422)			(0.0161)		
Low		-0.549***	-0.598***		-0.0810*	-0.100*		-0.0523***	-0.0317
		(0.121)	(0.226)		(0.0445)	(0.0548)		(0.0164)	(0.0202)
High		-1.910***	-1.020***		-0.459***	-0.210***		-0.128***	-0.0865***
		(0.316)	(0.152)		(0.0936)	(0.0529)		(0.0367)	(0.0200)
Pre-treatment mean	3.91			1.87			0.47		
p-value for equality		0.00	0.11		0.00	0.15		0.06	0.05
Pre-treatment-low mean		3.30	1.93		1.76	0.88		0.44	0.22
Pre-treatment-high mean		5.52	4.85		2.16	2.34		0.56	0.60
Observations	23,148	23,148	23,148	23,148	23,148	23,148	23,148	23,148	23,148
Number of clusters	643	643	643	643	643	643	643	643	643

Notes: This table reports event study estimates using the Borusyak et al. (2024) two-step imputation method. Standard errors (in parentheses) are clustered at the network level: * p < 0.10, ** p < 0.05, *** p < 0.01.

In short, the police should target active players who are also more central, since these offenders generate large spillover effects on their peers.

6 Learning about the Probability of Conviction

6.1 Theory

In this section, we examine how offenders update their beliefs about the probability of conviction and how these updates influence their criminal behavior, particularly in response to the removal of a network member. Recall that in Section 2, we assumed that the cost of being caught and convicted was exogenous to the criminal, implying that offenders did not revise their beliefs about the probability of being caught following the death of a co-offender. We now relax this assumption, by allowing the offenders' perceptions of the cost of being caught and convicted to be influenced by their network interactions and observations.

In the revised model, with probability p, an agent is convicted and punished with a fine *or* prison sentence, f, resulting in the utility loss of $-p\, f\, y_{it}$. This punishment has a deterrent effect on crime. While the true p may be fixed, an individual's *perceived* p is, in part, determined through peer observations. Do peers get caught and convicted often? If so, what punishments do they receive? Thus, an offender's expected probability of being convicted becomes a weighted average of their prior beliefs and the observed outcomes within their network, expressed as:

$$E[p]_{it} = \alpha p_{i0} + (1-\alpha)\sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt},$$

where $\widehat{g}_{ijt} = g_{ijt}/d_{it}$, with d_{it} being the degree of criminal i at time t (that is, the number of criminal friends), and p_{i0} is the initial perceived probability of being convicted based on solo offenses. In this formulation, $\alpha > 0$ captures the weight individual i puts on initial beliefs versus updated perceptions from peer outcomes.

Assuming that the punishment f and probability p are independent and that uncertainty arises only about the probability of being convicted p (f is known with certainty), the expected cost of being caught becomes:

$$E[p]_{it}\, E[f|p]_{it} = \left[\alpha p_{i0} + (1-\alpha)\sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt}\right] f. \tag{11}$$

In equilibrium, offenders simultaneously choose how many crimes to commit, $y_{it} \geq 0$, in order to maximize their expected utility given by (1). Criminals take $\boldsymbol{y}_t$ and $\boldsymbol{G}_t$ as given when making this decision. Using (11), the updated utility function (1) can now be written as:

$$\begin{aligned} E[u_{it}(\boldsymbol{y}_t, \boldsymbol{G}_t)] &= (x_i + \epsilon_{it} + \eta_t)\, y_{it} - \frac{1}{2} y_{it}^2 - E[p]_{it}\, E[f|p]_{it}\, y_{it} + \phi \sum_{j=1}^{n} g_{ijt} y_{it} y_{jt}. \\ &= (x_i + \epsilon_{it} + \eta_t)\, y_{it} - \frac{1}{2} y_{it}^2 - \left[\alpha p_{i0} + (1-\alpha) \sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt} \right] f\, y_{it} + \phi \sum_{j=1}^{n} g_{ijt} y_{it} y_{jt}. \end{aligned}$$

The best-reply function for each agent $i = \{1, \ldots, n\}$ is equal to

$$y_{it} = \phi \sum_{j=1}^{n} g_{ijt} y_{jt} + x_i + \eta_t + \epsilon_{it} - \alpha f p_{i0} - (1-\alpha) f \sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt}. \tag{12}$$

In matrix form, this can be written as

$$\mathbf{y}_t = \phi \boldsymbol{G}_t \mathbf{y}_t + \mathbf{x} + \eta_t \mathbf{1} + \boldsymbol{\epsilon_t} - \alpha f \mathbf{p}_0 - (1-\alpha) f \widehat{\boldsymbol{G}}_t \mathbf{p}_t,$$

where $\widehat{\boldsymbol{G}}_t$ is the row-normalized matrix of $\boldsymbol{G}_t$. By solving this equation, we obtain:

$$\mathbf{y}_t = (\mathbf{I} - \phi \boldsymbol{G}_t)^{-1} \left[\mathbf{x} + \eta_t \mathbf{1} + \boldsymbol{\epsilon}_t - \alpha f \mathbf{p}_0 - (1-\alpha) f \widehat{\boldsymbol{G}}_t \mathbf{p}_t \right]. \tag{13}$$

Next, we consider we analyze the effect of removing a criminal k on remaining offenders' criminal behavior. The change in criminal effort for any offender i is:

$$y_{it}^{-[k]} - y_{it} = \underbrace{\phi \left(\sum_{j=1}^{n} g_{ijt}^{-[k]} y_{jt}^{-[k]} - \sum_{j=1}^{n} g_{ijt} y_{jt} \right)}_{\text{spillover effect}} - \underbrace{(1-\alpha) f \left(\sum_{j=1}^{n} \widehat{g}_{ijt}^{-[k]} p_{jt}^{-[k]} - \sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt} \right)}_{\text{perceived probability of conviction effect}}.$$

In matrix form, this can be written as

$$\mathbf{y}_t^{-[k]} - \mathbf{y}_t = \phi \left(\boldsymbol{G}_t^{-[k]} \mathbf{y}_t^{-[k]} - \boldsymbol{G}_t \mathbf{y}_t \right) - (1-\alpha) f \left(\widehat{\boldsymbol{G}}_t^{-[k]} \mathbf{p}_t^{-[k]} - \widehat{\boldsymbol{G}}_t \mathbf{p}_t \right),$$

where the superscript $-[k]$ refers to the network with criminal k removed. In particular, the adjacency matrix $\boldsymbol{G}_t^{-[k]}$ is constructed by removing from $\boldsymbol{G}_t$ the row and column corresponding to k.

The key question is whether the removal of a criminal k in the network decreases the criminal effort of criminal i. When criminal k dies, then clearly $\sum_{j=1}^{n} g_{ijt}^{-[k]} y_{jt}^{-[k]} < \sum_{j=1}^{n} g_{ijt} y_{jt}$ because of strategic complementarities (Ballester et al., 2006). This effect, discussed in Section 2, is referred to as the *spillover effect*. However, it is not clear whether $\sum_{j=1}^{n} \widehat{g}_{ijt}^{-[k]} p_{jt}^{-[k]} - \sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt}$ is positive or negative. This term represents the *perceived probability of conviction effect*, the sign of which depends upon whether removing criminal k reduces or increases i's perceived probability of being convicted. We summarize these effects in the following proposition:

Proposition 4. *Assume $\phi\mu_1(\boldsymbol{G}_t) < 1$. If criminal k is removed from the network, three cases may arise:*

- (i) *Criminal k is not a direct co-offender of i (i.e., $g_{ikt} = 0$). Then, $y_{it}^{-[k]} < y_{it}$, $\forall i$, which means that criminal i reduces their effort when k dies. Moreover, the further away in the network was criminal k from i, the smaller is this reduction in effort.*
- (ii) *Criminal k is a co-offender of i (i.e., $g_{ikt} = 1$) and, for at least one criminal i, $\sum_{j=1}^{n} \widehat{g}_{ijt}^{-[k]} p_{jt}^{-[k]} > \sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt}$, while for all the other criminals in the remaining network $\sum_{j=1}^{n} \widehat{g}_{ijt}^{-[k]} p_{jt}^{-[k]} = \sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt}$. Then, $y_{it}^{-[k]} < y_{it}$, $\forall i$, which means that all criminals reduce their effort when k dies.*
- (iii) *Criminal k is a co-offender of i (i.e., $g_{ikt} = 1$) and $\sum_{j=1}^{n} \widehat{g}_{ijt}^{-[k]} p_{jt}^{-[k]} < \sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt}$, $\forall i$. Then, $y_{it}^{-[k]} \gtreqless y_{it}$, which means that criminal i reduces (increases) their effort when k dies if the perceived probability of conviction effect, $(1-\alpha) f\left(\sum_{j=1}^{n} \widehat{g}_{ijt}^{-[k]} p_{jt}^{-[k]} - \sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt}\right)$, is smaller (greater) than the spillover effect $\phi\left(\sum_{j=1}^{n} g_{ijt}^{-[k]} y_{jt}^{-[k]} - \sum_{j=1}^{n} g_{ijt} y_{jt}\right)$.*

Removing criminal k from a network automatically reduces the criminal effort of all other criminals, including those who are not linked to k, since they receive fewer spillovers from their co-offenders. In particular, if the deceased criminal is *not* a co-offender of criminal i, then spillovers are reduced, and the probability of being convicted is not affected; thus, criminal i reduces their effort (part (i) of Proposition 4).

If criminal i is a co-offender of k, then the removal of k also affects $\sum_{j=1}^{n} \widehat{g}_{ijt}^{-[k]} p_{jt}^{-[k]}$, the expected probability of being convicted. If, for at least some criminals, the perceived probability of conviction increases after the removal of k, while for others it is not affected (part (ii) of Proposition 4), then all criminals reduce their effort. If the opposite is true, that is, for all criminals the (expected) probability of being convicted increases after criminal k dies (part (iii) of Proposition 4), then the net effect on criminal effort is ambiguous and depends on how large the change in the perceived probability of conviction is compared to the spillover effect.

In Appendix B, we provide several examples that illustrate the distinct cases outlined in Proposition 4. These examples serve to clarify the theoretical framework and offer key insights into the intuition behind the results.

6.2 Empirical investigation

Our theoretical model predicts that if the death of a co-offender leads to an increase in the perceived probability of being convicted, $E[p]$, then offenders will decrease their criminal activity beyond the reduction caused by strategic complementarities. Conversely, if the probability of conviction is perceived to decrease, then offenders will increase their criminal activity in response to this. But the size and the sign of the overall change in crime will depend on the size of this change in perceived risk versus the size of the crime reducing spillover effects due to strategic complementarities.

To empirically explore these predictions, we first construct a measure of how often offenders are caught and convicted. While we do not observe the total number of crimes committed by an offender, we do observe the number of crimes that they are suspected of. Furthermore, we can observe if they were convicted of these crimes. For each offender, we calculate a proxy for the probability of being convicted, P, as follows. We divide the number of convictions that an offender has received by the number of times they have been suspected of a crime. Thus, a value of P equal to one indicates that the offender is always convicted when suspected, while a value of P equal to zero implies that they are never convicted. The sample mean of P is 0.32; 36% of the sample have a P equal to 0, while 10% have a P equal to 1.

In the context of co-offender deaths, a key mechanism at play is the loss of an additional channel for gaining new information in the future. That is, the death of a co-offender shrinks the future information set by one person. This will not matter if the deceased co-offender had an average P. However, it will matter if the deceased co-offender was an outlier who provided the network with extreme information signals. The key assumption here is that the deceased co-offender would have continued to supply "outlier" information to the network had they remained alive.

To empirically test this mechanism, we focus on a sample of one-step away co-offenders who have experienced a co-offender death. For this group, we calculate the change in the average P that they experience after the death of a co-offender, $\Delta\bar{P}$. To investigate potential heterogeneity in effects, we then split this sample into two groups: those with positive and those with negative values of $\Delta\bar{P}$, and estimate static DiD regressions for each group separately.

In line with our theoretical predictions, we find that there is a larger reduction in criminal outcomes for those offenders experiencing a positive $\Delta\bar{P}$ (see Panel (a) in Table 7) than those who experience a negative $\Delta\bar{P}$ (see Panel (b) in Table 7). These differences are statistically significant and hold across all outcomes, underlining the importance of perceived conviction probabilities in shaping criminal behavior.

7 Mechanisms

Our theoretical framework provides us with a set of mechanisms that explain the reduction in crime observed in our data following the death of a co-offender.

The loss of a co-offender reduces overall crime among surviving offenders due to strategic complementarities. Importantly, we find that deceased co-offenders are not fully replaced by new ones, resulting in a permanent reduction in crime. This finding is significant, as it challenges the common belief that arrested or removed co-offenders can and will be quickly replaced. Our data clearly indicate that this is not the case. More generally, forming new co-offending relationships is likely a time-consuming process that entails significant costs and risks.

Our findings also suggest that the concept of strategic complementarities encompasses multiple

Table 7: DiD Results - Experiencing Changes in the Perceived Probability of Conviction, $E[p]$

(a) Experiencing a Positive $\Delta\bar{P}$

	(1) Offenses	(2) Co-Offenses	(3) Solo-Offenses	(4) Co-Offenders	(5) Conviction No prison	(6) Conviction Prison
DiD	-0.368***	-0.191***	-0.177***	-0.251***	-0.050***	-0.019***
	(0.058)	(0.022)	(0.046)	(0.022)	(0.010)	(0.005)
Observations	23,100	23,100	23,100	23,100	23,100	23,100
number of clusters	654	654	654	654	654	654
p-value no pre-trends	0.290	0.154	0.644	0.169	0.737	0.569
pre-treatment mean	0.534	0.139	0.395	0.176	0.086	0.021

(b) Experiencing a Negative $\Delta\bar{P}$

	(1) Offenses	(2) Co-Offenses	(3) Solo-Offenses	(4) Co-Offenders	(5) Conviction No prison	(6) Conviction Prison
DiD	-0.257***	-0.129***	-0.128***	-0.228***	-0.038***	-0.010***
	(0.049)	(0.018)	(0.040)	(0.023)	(0.010)	(0.004)
Observations	20,825	20,825	20,825	20,825	20,825	20,825
number of clusters	557	557	557	557	557	557
p-value no pre-trends	0.188	0.675	0.162	0.034	0.266	0.947
pre-treatment mean	0.685	0.169	0.516	0.208	0.095	0.025
p-value of Wald test:	0.111	0.062	0.049	0.023	0.013	0.008

This table reports DiD estimates of τ in equation (9) using the Borusyak et al. (2024)'s two-step imputation method. The sample includes offenders who have experienced a one-step away co-offender death. Standard errors (in parentheses) are clustered at the individual level: * p < 0.10, ** p < 0.05, *** p < 0.01.

mechanisms. The loss of a co-offender reduces both co-offenses and solo-offenses among surviving offenders. The reduction in crime is particularly pronounced in co-offenses, where the need for collaboration is inherent. The reduction in solo-offenses suggests that complementarities extend beyond direct cooperation to include less tangible forms, such as the loss of information about criminal opportunities, the absence of a role model, or changes in the social norms within the group that influence criminal activity.

The larger decrease in co-offenses compared to solo-offenses also suggests that some offenders either require or prefer the presence of another person to commit certain crimes. For these offenders, the absence of a potential co-offender restricts the execution of crimes that require multiple individuals. The need or preference for working together arises in addition to the other forms of complementarities mentioned above.

The loss of a co-offender also affects the future information set of offenders, potentially altering their perceptions of the probability of being convicted if caught. These shifts in perception can either decrease or increase criminal behavior by changing the expected value of committing a crime.

Finally, structural properties of co-offending networks, such as network connectivity and network centrality, are crucial in facilitating the spread of criminal activities across social space. An understanding of the structure of these networks can be leveraged to disrupt the propagation of crime and, hence, reduce overall crime in society.

8 Conclusion

Understanding the impact of social interactions and network effects on crime can inform more effective interventions and policies. In this paper, we provide causal estimates of spillover effects in criminal activity by leveraging the permanent removal of a co-offender due to death. Spillover effects are substantial and their influence does not just affect direct co-offenders, but also individuals two and three steps removed from the deceased offender. These effects are present in all of the crime types that we study: solo-offenses, co-offenses, and convictions with and without prison sentences. We also show that there is a permanent reduction in the number of individuals that an offender co-offends with. Co-offenders are not fully replaced, which leads to a permanent reduction in the number of crimes committed. We view this set of findings as lending support to exit strategies and relocation policies that permanently remove offenders from their co-offending networks.

Our results also show that removing a more central co-offender generates larger spillover effects and larger absolute reductions in crime than the removal of a less central co-offender. Importantly, the removal of a highly central individual reduces crime by more than the removal of a less well-connected but highly active offender who has committed many crimes. This result is due to the large crime-reducing spillover effects generated by the removal of a high centrality offender. We view these findings as strong evidence in favor of the use of focused deterrence strategies that leverage measures of network centrality when choosing which offenders to target.

Finally, our empirical evidence also shows that perceptions of the probability of being convicted do matter. Thus, policies that increase the perceived risk of conviction among crime-prone populations may also serve as an effective tool to lower crime. Altogether, our findings not only advance our understanding of the mechanisms through which networks influence criminal behavior, but also offer concrete policy insights on how information about the structure of social networks can be used to combat criminal activity more effectively.

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Appendix

A Additional figures and tables

Figure A1: The Share of Offenders that Die Each Month

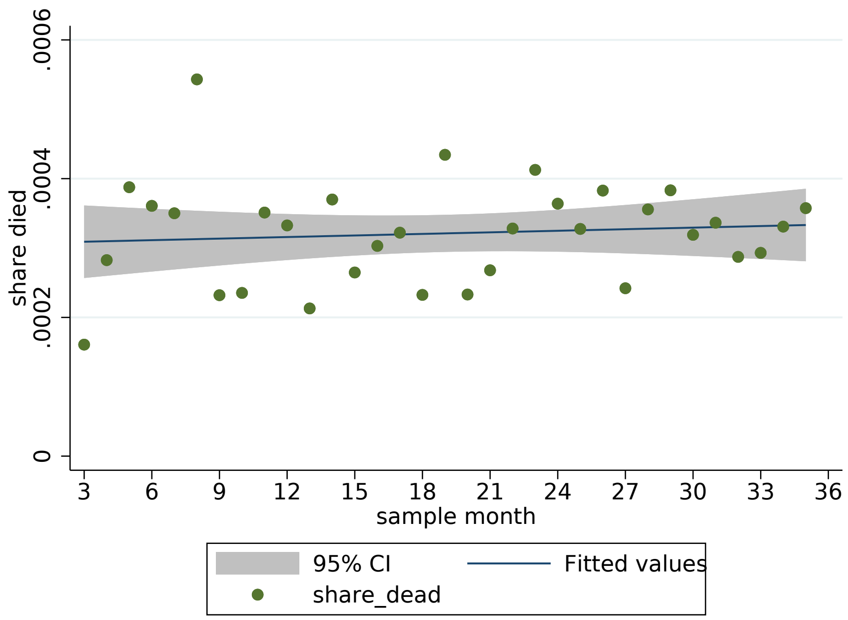
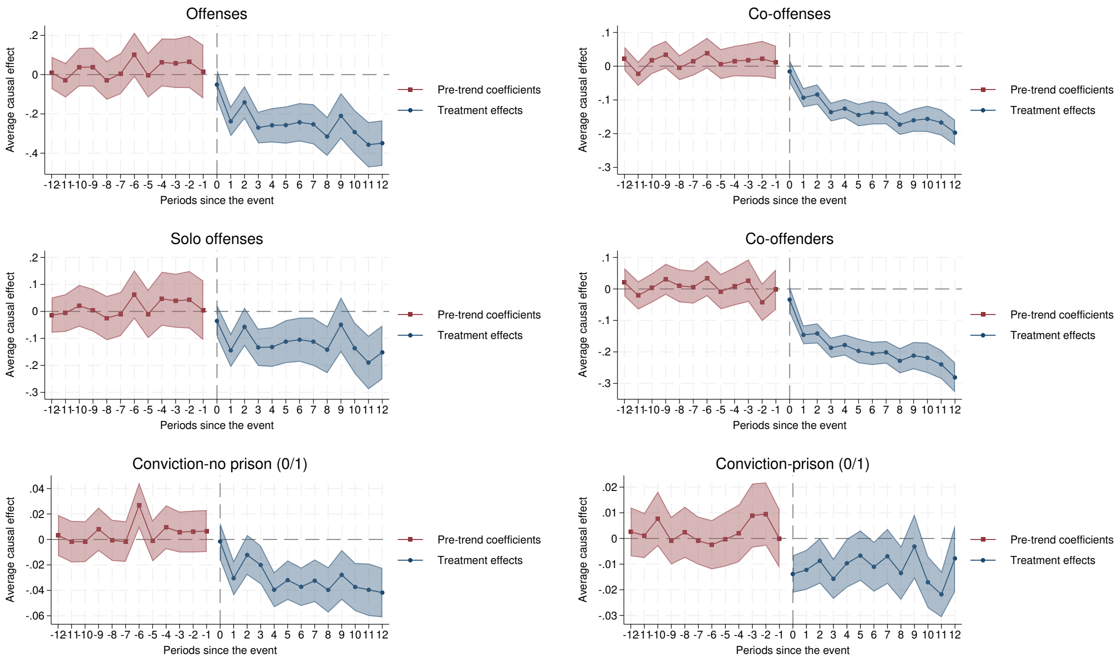


Figure A2: Impact of one-step away deaths (excluding never treated).



Notes: The figures plot estimates of the dynamic DiD model in equation 8 for one-step away deaths estimated using the Borusyak et al. (2024) two-step imputation method in a sample that excludes never-treated cooffenders. 5% confidence intervals are shown, using standard errors clustered at the offender i level.

Table A1: The Impact of Single-Death Events on the Crime Outcomes of Former Peers

(a) One-Step away deaths

	(1) Offenses	(2) Co-Offenses	(3) Solo-Offenses	(4) Co-Offenders	(5) Conviction No prison	(6) Conviction Prison
DiD	-0.215***	-0.123***	-0.092***	-0.203***	-0.035***	-0.008***
	(0.020)	(0.009)	(0.015)	(0.012)	(0.005)	(0.002)
Observations	3,642,516	3,642,516	3,642,516	3,642,516	3,642,516	3,642,516
number of clusters	101,180	101,180	101,180	101,180	101,180	101,180
p-value no pre-trends	0.253	0.194	0.582	0.005	0.172	0.931
pre-treatment mean	0.384	0.105	0.279	0.144	0.060	0.015

(b) Two-Step away deaths

	(1) Offenses	(2) Co-Offenses	(3) Solo-Offenses	(4) Co-Offenders	(5) Conviction No prison	(6) Conviction Prison
DiD	-0.046**	-0.019***	-0.027	-0.034***	-0.009**	-0.002
	(0.023)	(0.007)	(0.018)	(0.010)	(0.004)	(0.002)
Observations	3,656,916	3,656,916	3,656,916	3,656,916	3,656,916	3,656,916
number of clusters	101,578	101,578	101,578	101,578	101,578	101,578
p-value no pre-trends	0.045	0.410	0.017	0.004	0.426	0.003
pre-treatment mean	0.432	0.107	0.325	0.146	0.068	0.016

(c) Three-Step away deaths

	(1) Offenses	(2) Co-Offenses	(3) Solo-Offenses	(4) Co-Offenders	(5) Conviction No prison	(6) Conviction Prison
DiD	-0.013	-0.004	-0.008	-0.032***	-0.001	-0.003**
	(0.013)	(0.005)	(0.011)	(0.008)	(0.003)	(0.001)
Observations	3,726,072	3,726,072	3,726,072	3,726,072	3,726,072	3,726,072
number of clusters	103,488	103,488	103,488	103,488	103,488	103,488
p-value no pre-trends	0.266	0.673	0.166	0.031	0.511	0.274
pre-treatment mean	0.437	0.113	0.324	0.175	0.068	0.017

Notes: This table reports DiD estimates for offenders who have experienced only unique events, using the Borusyak et al. (2024). two-step imputation method. Standard errors (in parentheses) are clustered at the individual level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Robustness checks: 1-Step Away Deaths

	(1) Offenses	(2) Co-Offenses	(3) Solo-Offenses	(4) Co-Offenders	(5) Convictions no prison	(6) Convictions prison
Panel A. Excluding deaths of under 18 and above 65						
DiD	-0.282***	-0.138***	-0.144***	-0.208***	-0.036***	-0.010***
	(0.024)	(0.009)	(0.020)	(0.010)	(0.005)	(0.002)
Observations	3,859,344	3,859,344	3,859,344	3,859,344	3,859,344	3,859,344
Panel B. Excluding deaths related to narcotics and alcohol						
DiD	-0.206***	-0.112***	-0.093***	-0.201***	-0.021***	-0.007***
	(0.024)	(0.011)	(0.019)	(0.018)	(0.005)	(0.003)
Observations	3,838,176	3,838,176	3,838,176	3,838,176	3,838,176	3,838,176
Panel C. Only deaths caused by accidents unrelated to alcohol or narcotics						
DiD	-0.229***	-0.120***	-0.110***	-0.226***	-0.023**	0.000
	(0.060)	(0.032)	(0.040)	(0.052)	(0.011)	(0.002)
Observations	3,821,652	3,821,652	3,821,652	3,821,652	3,821,652	3,821,652
Panel D. Excluding deaths preceded by long hospitalizations						
DiD	-0.276***	-0.139***	-0.137***	-0.220***	-0.038***	-0.007***
	(0.024)	(0.010)	(0.019)	(0.013)	(0.005)	(0.002)
Observations	3,853,764	3,853,764	3,853,764	3,853,764	3,853,764	3,853,764

Notes: This table reports DiD estimates of tau in equation 9 for one-step away deaths using the Borusyak et al. (2024)'s two-step imputation method. The first panel excludes deaths of under 18 and above 65, the second panel excludes deaths related to narcotics and alcohol, the third panel only includes deaths caused by accidents unrelated to alcohol or narcotics, and the fourth panel excludes deaths preceded by long hospitalizations (more than 5 days). Standard errors (in parentheses) are clustered at the individual level: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A3: Placebo: 1-Step Away Deaths

	(1) Offenses	(2) Co-Offenses	(3) Solo-Offenses	(4) Co-Offenders	(5) Convictions no prison	(6) Convictions prison
Panel A. Baseline DiD estimates						
DiD	-0.248***	-0.136***	-0.112***	-0.216***	-0.034***	-0.010***
	(0.021)	(0.009)	(0.017)	(0.012)	(0.005)	(0.002)
Panel B. Placebo (100 iterations)						
Average	-0.001	-0.001	0.000	-0.001	0.000	0.000
SD	0.013	0.005	0.010	0.010	0.003	0.001
(Min,Max)	(-0.034,0.029)	(-0.012,0.012)	(-0.026,0.028)	(-0.036,0.024)	(-0.009,0.005)	(-0.002,0.002)
Observations	3,860,280	3,860,280	3,860,280	3,860,280	3,860,280	3,860,280

Notes: Sample includes offenders who have experienced a single one-step away death of a co-offender. In Panel A, we report DiD estimates of tau in equation 7 for one-step away deaths using the Borusyak et al. (2024)'s two-step imputation method. In Panel B, we report a placebo exercise in which we randomly reshuffling the events (death of a one-step away co-offender) across offenders in this sample, while maintaining the total number and timing distribution of the events constant. We then estimate 100 iterations of the static difference-in-differences specification (equation 9) and report summary statistics of the obtained coefficients.

B Examples illustrating Proposition 4

Consider the following network:

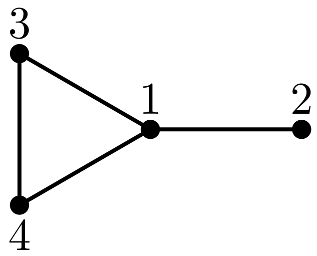


Figure A3: Specific network

That is,

$$\boldsymbol{G}_t = \begin{pmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{pmatrix}, \quad \widehat{\boldsymbol{G}}_t = \begin{pmatrix} 0 & 0.333 & 0.333 & 0.333 \\ 1 & 0 & 0 & 0 \\ 0.5 & 0 & 0 & 0.5 \\ 0.5 & 0 & 0.5 & 0 \end{pmatrix}.$$

Clearly, agent 1 is the most central, while agent 2 is the least central. Assume the following parameters:

$$\phi = 0.2,\ x_i + \epsilon_{it} + \eta_t = 1 \text{ for all } i,\ \alpha = 0.1,\ f = 1,$$

and

$$\mathbf{p}_0 = \begin{pmatrix} 0.2 \\ 0.2 \\ 0.2 \\ 0.2 \end{pmatrix}, \quad \mathbf{p} = \begin{pmatrix} 0.5 \\ 0.1 \\ 0.4 \\ 0.4 \end{pmatrix}.$$

This assumes that all criminals think they have the same *prior probability of being convicted* (based on their solo-offenses) and put a very large weight (90%) on the deterrence effect based on their co-offenders' probability of being convicted. Agent 1 is assumed to have a higher chance to be convicted, followed by 3 and 4, and then by 2. This implies that the expectation of being convicted for each criminal is given by

$$\alpha f \mathbf{p}_0 + (1-\alpha)\widehat{\boldsymbol{G}}_t \mathbf{p}_t = \begin{pmatrix} 0.28 \\ 0.44 \\ 0.40 \\ 0.40 \end{pmatrix}.$$

Criminal 1 believes they have the lowest chance to be convicted because they are linked to agent 2, who has a very low probability, while the other criminals have a higher expected probability of being convicted because they are all linked to criminal 1. Note that

$$\widehat{\boldsymbol{G}}_t \mathbf{p}_t = \sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt} = \begin{pmatrix} 0.3 \\ 0.5 \\ 0.45 \\ 0.45 \end{pmatrix}.$$

It is straightforward to show that the equilibrium criminal efforts are given by

$$\mathbf{y}_t = (\mathbf{I} - \phi \boldsymbol{G}_t)^{-1} \left(\mathbf{x} + \boldsymbol{\epsilon}_t + \eta_t \mathbf{1} - \alpha f \mathbf{p}_0 - (1-\alpha) \widehat{\boldsymbol{G}}_t \mathbf{p} \right) = \begin{pmatrix} 1.283 \\ 0.787 \\ 1.040 \\ 1.040 \end{pmatrix}.$$

Not surprisingly, criminal 1 makes the highest effort (positive spillovers due to complementarities and lowest beliefs of being convicted) while criminal 2 makes the lowest effort.

Case 1: Criminal 2 dies

When criminal 2 dies, the network becomes

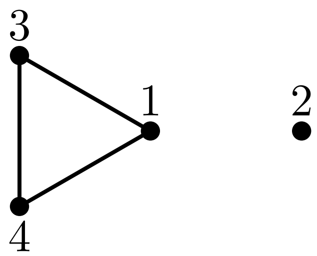


Figure A4: Remaining network when criminal 2 dies

The remaining network is thus given by the complete network of three agents, that is,

$$\boldsymbol{G}_t^{-[2]} = \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{pmatrix}, \ \widehat{\boldsymbol{G}}_t^{-[2]} = \begin{pmatrix} 0 & 0.5 & 0.5 \\ 0.5 & 0 & 0.5 \\ 0.5 & 0.5 & 0 \end{pmatrix}.$$

This implies that the expectation of being convicted for each agent is given by

$$\sum_{j=1}^{n} \widehat{g}_{ijt}^{-[2]} p_{jt}^{-[2]} = \begin{pmatrix} 0.4 \\ 0.45 \\ 0.45 \end{pmatrix},$$

while it was previously given by

$$\sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt} = \begin{pmatrix} 0.3 \\ 0.45 \\ 0.45 \end{pmatrix}.$$

Thus, criminal 1 now thinks they have a *higher chance* of being convicted (from 0.3 to 0.4), while criminals 3 and 4 have the *same* expectation of being convicted because they were not linked to agent 2. Since $\sum_{j=1}^{n} \widehat{g}_{ijt}^{-[2]} p_{jt}^{-[2]} \geq \sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt}$, for all $i = 1, 2, 3, 4$, we are in cases (i) and (ii) of Proposition 4 and thus all criminals reduce their effort. Indeed, it is easily verified that

$$\mathbf{y}_t^{-[2]} = \begin{pmatrix} 1.108 \\ 0.996 \\ 0.996 \end{pmatrix}.$$

Compared to

$$\mathbf{y}_t = \begin{pmatrix} 1.283 \\ 1.040 \\ 1.040 \end{pmatrix},$$

all criminals reduce their efforts. Indeed,

$$\mathbf{y}_t^{-[2]} - \mathbf{y}_t = \begin{pmatrix} -0.175 \\ -0.044 \\ -0.044 \end{pmatrix}.$$

This is because all criminals obtain less spillovers and either their probability of being convicted increases (for criminal 1) or stays the same (for criminals 3 and 4). Since criminals 3 and 4 did not co-offend with 2, their reduction in effort (4.42%) is lower than that of criminal 1 (15.8%), who was a co-offender of 2.

Case 2: Criminal 4 dies

When criminal 4 dies, the network becomes

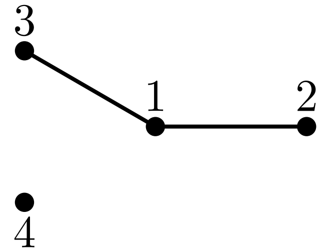


Figure A5: Network when criminal 4 dies

Thus, the network is now given by the star network, that is,

$$\boldsymbol{G}_t^{-[4]} = \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}, \; \widehat{\boldsymbol{G}}_t^{-[4]} = \begin{pmatrix} 0 & 0.5 & 0.5 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}.$$

The equilibrium crime efforts are equal to:

$$\mathbf{y}_t^{-[4]} = \begin{pmatrix} 1.051 \\ 0.740 \\ 0.740 \end{pmatrix},$$

while they were given by

$$\mathbf{y}_t = \begin{pmatrix} 1.283 \\ 0.787 \\ 1.040 \end{pmatrix},$$

so that

$$\mathbf{y}_t^{-[4]} - \mathbf{y}_t = \begin{pmatrix} -0.232 \\ -0.047 \\ -0.3 \end{pmatrix}.$$

Let's us explain why all effort decrease. First, observe that

$$\sum_{j=1}^{n} \widehat{g}_{ijt}^{-[4]} p_{jt}^{-[4]} = \begin{pmatrix} 0.25 \\ 0.5 \\ 0.5 \end{pmatrix},$$

which they were previously given by

$$\sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt} = \begin{pmatrix} 0.3 \\ 0.5 \\ 0.45 \end{pmatrix}.$$

Criminal 1 now thinks they have a *lower* chance of being convicted (from 0.3 to 0.25), criminal 2 believes they have the *same chance* of being convicted (0.5), and, finally, agent 3 thinks they have a *higher* chance to be convicted (from 0.45 to 0.5). This implies that for agent 1, $\sum_{j=1}^{n} \widehat{g}_{1jt}^{-[4]} p_{jt}^{-[4]} < \sum_{j=1}^{n} \widehat{g}_{1jt}^{-[4]} p_{jt}^{-[4]}$ (part (iii) of Proposition 4) while for players 2 and 3, we have $\sum_{j=1}^{n} \widehat{g}_{ijt}^{-[4]} p_{jt}^{-[4]} \geq \sum_{j=1}^{n} \widehat{g}_{ijt}^{-[4]} p_{jt}^{-[4]}$, for $i = 2, 3$ (parts (i) and (ii) of Proposition 4). Thus, the criminal efforts of criminals 2 and 3 decrease. What about criminal 1? We have

$$\begin{aligned}
y_{1t}^{-[4]} - y_{1t} &= \phi\left(\sum_{j=1}^{n} g_{1jt}^{-[4]} y_{jt}^{-[4]} - \sum_{j=1}^{n} g_{1jt} y_{jt}\right) - (1-\alpha) f \left(\sum_{j=1}^{n} \widehat{g}_{1jt}^{-[4]} p_{jt}^{-[4]} - \sum_{j=1}^{n} \widehat{g}_{1jt} p_{jt}\right) \\
&= 0.2\left[y_{2t}^{-[4]} + y_{3t}^{-[4]} - (y_{2t} + y_{3t} + y_{4t})\right] - 0.9\left[\frac{p_{2t}^{-[4]} + p_{3t}^{-[4]}}{2} - \frac{(p_{2t} + p_{3t} + p_{4t})}{3}\right] \\
&= 0.2\left((0.74 + 0.74) - (0.787 + 1.04 + 1.04)\right) - 0.9\,(0.25 - 0.3) \\
&= -0.232.
\end{aligned}$$

Criminal 1 reduces their effort but what is interesting is that there is now a *trade off*. On the one hand, agent 1 thinks they have a *lower chance to be convicted* (from 0.3 to 0.25), so this means that they will increase their effort. On the other hand, because agent 4 dies, agent 1 gets *lower spillovers* (from $0.787 + 1.04 + 1.04 = 2.867$ to $0.74 + 0.74 = 1.48$), which decreases their effort. The net effect is negative, so criminal 1 decreases their effort.

Let us now illustrate case (i) of Proposition 4, that is, the impact of the death of criminal 4 on the effort of criminal 2, who is *not* a co-offender of 4. First, even if 4 is not connected to 2, removing 4 still reduces the spillover effect obtained by 2, because by removing criminal 4, 1 reduces their effort, which in turn negatively affects criminal 2. Because criminal 2 is two-links away from 4, the effect is not as important as the one on player 1 or player 3, who were co-offenders. Indeed, we see from (B) that criminals 1 and 3 reduce their effort by 23.2% and 40.5%, respectively, while, for criminal 2, the reduction is only 6.35%.

Case 3: Criminal 1 dies

When criminal 1 dies, the network becomes

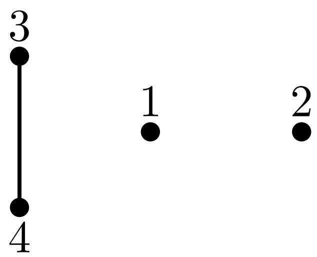


Figure A6: Remaining network when criminal 1 dies

Thus, we have the following remaining network

$$\boldsymbol{G}_t^{-[1]} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix}, \widehat{\boldsymbol{G}}_t^{-[1]} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix},$$

in which criminal 2 is now isolated while criminals 3 and 4 form a dyad. This implies that

$$\sum_{j=1}^{n} \widehat{g}_{ijt}^{-[1]} p_{jt}^{-[1]} = \begin{pmatrix} 0 \\ 0.4 \\ 0.4 \end{pmatrix},$$

while it was previously given by

$$\sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt} = \begin{pmatrix} 0.5 \\ 0.45 \\ 0.45 \end{pmatrix}.$$

The effect on criminal 2 is huge because they now believe they have zero chance of being convicted while, before criminal 1 died, criminal 2 believed that they had a 50% of being convicted. Thus, let us focus on the effect of the removal of 1 on their co-offender 2. We have:

$$0 = \sum_{j=1}^{n} \widehat{g}_{2jt}^{-[1]} p_{2t}^{-[1]} < \sum_{j=1}^{n} \widehat{g}_{2jt} p_{2t} = 0.5.$$

Thus, for player 2, we are in case (iii) of Proposition 4. This leads to

$$\begin{aligned} y_{2t}^{-[1]} - y_{2t} &= \phi \left(\sum_{j=1}^{n} g_{2jt}^{-[1]} y_{jt}^{-[1]} - \sum_{j=1}^{n} g_{2jt} y_{jt} \right) - (1-\alpha) f \left(\sum_{j=1}^{n} \widehat{g}_{2jt}^{-[1]} p_{jt}^{-[1]} - \sum_{j=1}^{n} \widehat{g}_{2jt} p_{jt} \right) \\ &= \phi \left(0 - y_{1t} \right) - (1-\alpha) f \left(0 - p_{1t} \right) \\ &= 0.2 \left(0 - 1.283 \right) - 0.9 \left(0 - 0.5 \right) \\ &= 0.193. \end{aligned}$$

In other words, when criminal 1 dies, co-offender 2 *increases* their criminal effort, that is, $y_{2t}^{-[1]} > y_{2t}$. Indeed, even though the decrease in deterrence is very large (it decreases by 0.5 from 0.5 to 0), the decrease in the spillover effect is even larger (it decreases by 1.283 from 1.283 to 0). However, the net effect of the removal of criminal 1 on criminal 2's effort is positive because criminal 2 puts a very large weight (0.9) on the deterrence effect while the intensity of the spillover effect is much smaller (0.2).

For the other two criminals, it is easily verified that

$$y_{3t}^{-[1]} - y_{3t} = y_{4t}^{-[1]} - y_{4t} = -0.265,$$

that is, for criminals 3 and 4, the removal of criminal 1 from the network leads to a *decrease* in their effort because of the strong loss of the spillover effect.