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ABSTRACT

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

We study spillover effects within co-offending networks by leveraging deaths of co-offenders for causal identification. Our results demonstrate that the death of a co-offender significantly reduces the criminal activities of other network members. We observe a decaying pattern in the magnitude of these spillover effects: individuals directly linked to a deceased 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. We also provide evidence consistent with a new theoretical prediction suggesting that the loss of a co-offender shrinks the future information set of offenders, altering their perceptions of the probability of being convicted and consequently affecting their criminal behavior. Our findings highlight the importance of understanding spillover effects for policymakers seeking to develop more effective strategies for crime prevention.

JEL Classification: A14, D85, K42, Z13

Keywords: networks, crime, key players, exogenous deaths, spillovers

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1 Introduction

Empirical research on crime has highlighted the importance of considering social interactions and community networks in understanding and addressing crime (Lindquist & Zenou, 2019; Gavrilova & Puca, 2022). Spillover effects in crime can manifest in various forms, affecting not only neighboring communities but also broader social, economic, and political contexts. Understanding how these spillover effects operate is crucial for developing effective crime prevention and mitigation strategies.

In this paper, we study the role of social interactions and social networks in the etiology of crime. Specifically, we estimate spillover effects in criminal behavior within co-offending networks by using co-offender deaths as a source of causal identification. These deaths allow us to examine whether and how offenders change their criminal behavior when one of their co-offenders is permanently removed from their co-offending network.

We address two main research questions. First, does the death of a co-offender affect the criminal behavior of the surviving members within the co-offending network? Second, does the magnitude of this effect depend on how well-connected the deceased co-offender was? In other words, do measures of network centrality help us predict which co-offenders will have the largest impact on crime after their removal from the network? We also explore a novel theoretical prediction concerning how the loss of a co-offender may affect the information available to surviving offenders regarding the probability of being convicted, and thereby influence their criminal activity.

We develop a network model in which offenders are connected when they are suspected of committing a crime together. Two key aspects characterize this model. First, each offender generates positive spillover effects on their co-offenders by, for instance, sharing crime-related information or helping each other commit crimes more effectively. Second, each offender infers their probability of being convicted from their own past experience as well as the experiences of their co-offenders.

We characterize the Nash equilibrium of this game and show that, under certain conditions, a unique interior solution exists. Then, we study the impact of the death of an offender, who is permanently removed from the network, on the criminal activities of all offenders in the remaining network. There are two effects at work. First, when an offender dies, all co-offenders experience reduced spillovers and consequently commit fewer crimes. Furthermore, the farther away a criminal is from the deceased individual, the smaller is the crime-reducing spillover effect. Second, when someone dies, all remaining offenders lose a source of future information regarding the probability of conviction if caught. If the death of a co-offender leads to an increase in the expected conviction rate, then surviving offenders may reduce their criminal efforts and commit fewer crimes. On the other hand, if the death of a co-offender leads to a decrease in the expected conviction rate, then two opposing effects operate. The death leads to a reduction in the spillover effect (and thus crime), while a lower expected conviction rate will encourage offenders to increase their criminal efforts. The net effect depends on the magnitude of the spillover effect, the relative size of the change in information, and the weight assigned to this change in information.

We test the predictions of this model using Swedish register data spanning the years 2010 to

2012. The Swedish Suspects Register contains information on all individuals suspected of committing a crime, 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 containing all co-offenders involved each crime for the years 2010 to 2012. We then transform this edge list into a complete set of co-offending networks.

The outcomes we consider include total (suspected) offenses, solo offenses, and co-offenses. We also track the number of unique co-offenders with whom a person engages in criminal activities. These outcome variables are sourced from the Swedish Suspects Register. In addition, we use data on convictions from the Swedish Convictions Register. From this data, we construct two mutually exclusive conviction variables: convictions that include a prison sentence (representing convictions for more serious crimes) and convictions that do not include a prison sentence (representing convictions for less serious crimes).

Between 2010 and 2012, we observe 679 deaths among our sample of 108,018 co-offenders. Statistics Sweden has provided us with the exact dates of death and the birth years of these individuals. We have also obtained the cause of death from the Swedish Cause of Death Register and hospitalization data from Sweden's Inpatient Register. We exclude 30 deaths due to assault, and use the remaining deaths as a source of exogenous variation in the structure of a treated network.

Our empirical analysis proceeds in three steps. In a first step, 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. Our identification strategy leverages a co-offender death as an exogenous shock to the structure of the network. The identification of a causal effect relies on the assumption that the exact timing of the death of a co-offender is conditionally exogenous to a surviving offender's criminal behavior. We provide strong evidence in support of this assumption. We also exclude deaths from assaults in our baseline analysis to further strengthen the likelihood that this assumption holds.

Our results illustrate 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 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 initial one-step away effect for co-offenses is much larger than the effect on solo-offenses, -94% versus -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 through exit strategies and/or relocation policies will have a permanent crime-reducing effect.

We show that these findings are robust to (1) excluding various different causes of death, (2) the age at which a co-offender dies, and (3) the amount of time a co-offender spends in the hospital in the months immediately preceding their death. As a placebo test, we conduct a randomization inference test, in which we show that the one-step away impact of reshuffled co-offender deaths generates a precisely estimated null effect.

We then explore the new theoretical prediction of our model concerning changes in an offender's expectation of the probability of being convicted after losing a source of information. We assign each individual a conviction probability, P, which is equal to the number of convictions an offender has received divided by the number of times an offender has been suspected of a crime. A P of zero means that the offender is never convicted, while a P of one means that the offender is always convicted. The average P across our full sample is 0.32. What happens when an offender loses a potential source of future information? On average, there should be (and is) no effect. However, when the loss of an offender leads to a large increase in $E[P]$, this leads to a small (but statistically significant) reduction in crime. Conversely, when the loss of an offender leads to a large decrease in $E[P]$, this leads to a small (but statistically significant) increase in crime.

We then 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 exercise focuses on measuring the total network-level spillover effect. In this exercise, we exclude the deceased offender's pre-mortem crime and study only the effect of their exclusion from the network on the crime activity of the surviving members of their network. We find that, on average, the death of a co-offender leads to an aggregate reduction of 9% for total offenses, 11% for co-offenses, 8% for solo-offenses, 11% for convictions with no prison sentence, and 17% for convictions with a prison sentence. The average number of co-offenders is reduced by 0.90 (0.282), which is equal to 24% of the pre-treatment mean.

We also show that the deaths of highly central offenders generate the largest total network-level spillover effects. In particular, losing a co-offender with many direct co-offending connections (i.e., high degree centrality) leads to the largest reductions in crime due to the large spillover effects that they generate. These effects are larger than those generated by deceased offenders with high eigenvector centrality (i.e., those with many indirect links), and larger than those generated by the most active offenders in their networks.

Our second network-level exercise is a "key player" exercise that tests a focused deterrence strategy. Who in the network should we remove to generate the largest reduction in aggregate crime? Here, we include the deceased co-offender and their pre-mortem crime in the network-level analysis. This way, their removal has two effects. We remove their crime, which may be large if they are a very active criminal, and we measure the total spillover effect they have on others in their network.

Our key player analysis boils down to a straightforward heterogeneity analysis, where we compare effects sizes across networks that randomly lose a highly central or active offender to those networks that randomly lose a less central or less active offender. For total offenses, we find that removing a high eigenvector centrality offender leads to a decrease that is nearly twice the size of the effect of removing an offender with a low eigenvector centrality (a test for equality yields a p-value of 0.03). Removing an offender with high degree centrality results in an effect size that is more than three times as large as the estimated decrease from removing a low degree centrality individual (p-value = 0.00). In addition, removing a highly active offender also leads to a larger decrease in total offenses than removing a less active offender (p-value = 0.03). The reduction from removing a high degree centrality individual is, on average, twice as large as the reduction from removing a highly active offender, due to the large spillover effects that they generate. In terms of the total reduction in offenses, degree centrality outperforms eigenvector centrality, which, in turn, outperforms a measure of criminal activity.

These findings are echoed to varying degrees across all outcomes, albeit with some nuances. For example, all three measures perform well when examining convictions with no prison sentences, and the relative performance ranking of the three measures does not change. In contrast to this, when looking at the results for convictions with prison sentences, only degree centrality appears to matter.

In our setting, degree centrality is the most powerful predictor of crime reductions since the one-step away spillover effects are much larger than the two- and three-step away spillover effects, and since very few of our networks are extremely large (i.e., with many two- and three-step away links). Together, these facts suggest that those with the largest number of direct co-offenders (degree centrality) will exert the largest influence over their co-offending network.

These findings provide causal evidence that the death of a more central co-offender leads to a larger reduction in aggregate crime compared to the death of a less central co-offender. Collectively, our findings at both the individual and network levels highlight the importance of understanding spillover effects for policymakers seeking to develop more effective crime-prevention strategies. They illustrate how the permanent removal of a co-offender through exit strategies and/or relocation policies can have a permanent crime-reducing effect. They also serve as a proof of concept for the use of network centrality measure when choosing which offenders should be targeted with focused deterrence strategies.

Related Literature The economics of crime literature has produced strong evidence demonstrating the importance of peer influence as a determinant of criminal and delinquent behavior.[1] The scope for peer influences may vary by crime type, as may the underlying mechanism.[2] We make several original contributions to this literature. We provide causal estimates of the spillover effect of perma-

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

[2] 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).

nently removing a co-offender from their co-offending network by leveraging co-offender deaths for causal identification.[3] Importantly, these network spillover effects exclude the potential deterrence effects that may be present in studies measuring the spillover effects of arrests and incarceration. This allows us to more clearly identify a specific set of social mechanisms.

We show that these spillover effects are large and that they extend 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 we move further away from the deceased co-offender. 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. There is a permanent reduction in the number of unique individuals that offenders co-offend with in the future, after losing one co-offender.

Our paper is also related to previous work 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 obtain the largest reduction in crime (Ballester et al., 2006, 2010; Lee et al., 2021). Key player policies consider not only how much crime an individual commits, but also the amount of social influence the person has over others. Some recent papers have evaluated key-player policies in different contexts. First, there is a literature that examines the importance of "central" agents in a network on different outcomes (Banerjee et al., 2013; Beaman et al., 2021; Mohnen, 2021; Zárate, 2023; Islam et al., 2024). The results showed that targeting the central (in terms of eigenvector or diffusion centrality) agents in a network increases diffusion. Second, there is a small literature directly testing the key-player centrality developed by Ballester et al. (2006). 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).

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 larger than those generated by removing the most active offender.[4] As such, we provide causal evidence, and a proof of concept, of the potential efficacy of focused deterrence strategies, offender exit policies, and offender relocation polices. Importantly, we do this using data and methods that

[3]Our strategy for causal identification is drawn from a broader literature that utilizes deaths as an exogenous source of variation to measure important economic phenomena. See, in particular, Jones & Olken (2005), Azoulay et al. (2010), Jaravel et al. (2018), Balsmeier et al. (2023), and Jäger & Heining (2024).

[4]Examples of such policies include the Boston Gun Project in 1995 and Operation Ceasefire in 1996 (Braga et al., 2001; 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 criminals.

are easy to understand and readily available to the police.

Lastly, we also provide new insights into how perceptions of the likelihood of being caught, convicted, and punished – 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 person.

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 results. We continue our individual level analysis in Section 5 by studying changes in offender behavior after experiencing changes in their information set concerning the probability of conviction. We present the results from our network level analysis in Section 6. 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, 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,[5] which describes the fixed architecture of the co-offender network at time t.

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 can be written as follows:

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

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 indi-

[5] Matrices and vectors are in bold while scalars are in normal letters.

vidual 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 with whom you commit crimes together with, 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 each co-offender exerts on each other (for example, learning about crime opportunities, on how to commit crime, etc.).

The new aspect of the model is the way we model the cost of being caught and convicted. Indeed, with probability p, an agent is convicted and punished with a fine *or* prison sentence f resulting in the utility loss $-p\,f\,y_{it}$. These costs have a deterrent effect on crime. While the actual p may be fixed, an individual's *perceived* p is, in part, learned through observing what happens to their peers. Do they get caught and convicted often? If so, what punishments do they receive? Thus, an offender's expected probability of being convicted can be written 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 for a criminal i at time 0 (based on solo crimes) and does not depend on peers being convicted. In this formulation, $\alpha > 0$ captures the weight individual i puts on p_{i0}, the initial belief criminal i has on the probability to be convicted at time $t = 0$ (their prior) versus the weight put at time t; α is the weight put on the prior. Importantly, at time t, criminal i evaluates their expected probability of conviction by looking at the average (expected) probability to be convicted of their criminal co-offenders; this is given by $\sum_{j=1}^{n}\widehat{g}_{ijt}p_{jt}$. In this formulation, p_{i0} could be the probability of being convicted when i commits solo-offences while $\sum_{j=1}^{n}\widehat{g}_{ijt}p_{jt}$ is the average probability of being convicted of i's co-offenders.

Assuming that the events f and p are independent and that the uncertainty is only on the probability of being convicted p (f is known with certainty), we have:

$$E[p]_{it}\,E[f|p]_{it} = \left[\alpha p_{i0} + (1-\alpha)\sum_{j=1}^{n}\widehat{g}_{ijt}p_{jt}\right] f. \tag{2}$$

In equilibrium, offenders simultaneously choose how many crimes to commit, $y_{it} \geq 0$, in order to maximize their own expected utility given by (1). Criminals take $\boldsymbol{y}_t$ and $\boldsymbol{G}_t$ into account when making this decision. Using (2), utility (1) can 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

$$y_{it} = \phi \sum_{j=1}^{n} g_{ijt} y_{jt} + x_i + \eta_t + \epsilon_{it} - \alpha f p_{i0} - (1-\alpha) f \sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt}. \tag{3}$$

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:

$$\mathbf{y}_t = (\mathbf{I} - \phi \boldsymbol{G}_t)^{-1} \left[\mathbf{x} + \eta_t \mathbf{1} + \boldsymbol{\epsilon}_t - \alpha f \mathbf{p}_0 - (1-\alpha) f \widehat{\boldsymbol{G}}_t \mathbf{p}_t\right]. \tag{4}$$

Denote by $\mu_1(\boldsymbol{A})$ the largest eigenvalue (spectral radius) of 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, which is given by (4). 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.*

2.1 Theoretical Predictions

We would like 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 have:

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

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 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 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 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 is the *deterrence effect*; the sign of which depends upon whether removing criminal k reduces or increases i's perceived probability of being convicted. We have the following result:

Proposition 2. *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 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 lower is this decrease 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 deterrence 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) that the spillover effect $\phi \left(\sum_{j=1}^{n} g_{ijt}^{-[k]} y_{jt}^{-[k]} - \sum_{j=1}^{n} g_{ijt} y_{jt} \right)$.*

For a given expected probability of being caught, more central criminals commit more crime than less central criminals (Ballester et al., 2006). This implies that, all else being equal, when high-centrality criminals die, they generate a larger reduction in crime in the network than less central criminals. This is due to strategic complementarities in efforts, which implies that high-centrality criminals generate more spillover effects to their co-offenders but also to all criminals in the network. Thus, removing a criminal k in a network automatically reduces the criminal effort of all criminals in the network, including those who are not linked to k, since they obtain less spillovers from their co-offenders. In particular, if the person who dies 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 2). If criminal i is a co-offender of k who dies, then the removal of k also affects $\sum_{j=1}^{n} \widehat{g}_{ijt}^{-[k]} p_{jt}^{-[k]}$, the expected probability of being convicted. When, for at least some criminals, the deterrence effect increases after the removal of k, while for others it is not affected (part (ii) of Proposition 2), 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 2), then the net effect of criminal effort is ambiguous and depends on how large is the deterrence effect compared to the spillover effect.

To illustrate this proposition, let us now provide a simple example.

2.2 Examples

2.2.1 Equilibrium

Consider the following network:

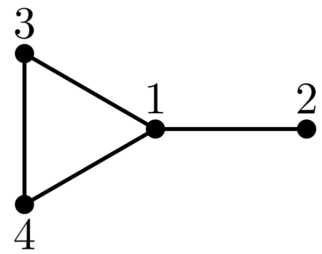


Figure 1: Specific network

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.

2.2.2 Removing one criminal from the network

Case 1: Criminal 2 dies

The remaining network is 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 2 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

The network is now given by the star network:

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

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

$$\mathbf{y}_t^{-[4]} - \mathbf{y}_t = \begin{pmatrix} -0.232 \\ -0.047 \\ -0.3 \end{pmatrix}. \tag{5}$$

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 2) 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 2)). Thus, the criminal efforts of criminals 2 and 3 decrease. What about criminal 1? We have

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

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 2, 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 (5) 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

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 2. 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.

2.3 Summary and testable predictions

From Proposition 2, we have four main testable predictions:

(i) When a criminal i dies, all their co-offenders should decrease their criminal effort (that is, commit less crimes) if $\sum_{j=1}^{n} \widehat{g}_{ijt}^{-[k]} p_{jt}^{-[k]} \geq \sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt}$.

(ii) When a criminal k dies, criminals who are not k's co-offenders may reduce their crime but this decrease should be smaller than that for the co-offenders of k.

(iii) When a criminal i dies, their co-offenders may increase their criminal effort if $\sum_{j=1}^{n} \widehat{g}_{ijt}^{-[k]} p_{jt}^{-[k]}$ $< \sum_{j=1}^{n} \widehat{g}_{ijt} p_{jt}$. This is not always true as it depends on the extent of the reduction in spillover effects. If the individual network centrality is not positively correlated with the probability of being convicted, then if a central person in the network dies, it is *less* likely that their co-offenders will increase their effort because of the large reduction in spillover effects.

(iv) All else being equal, when higher-centrality criminals die, they generate larger reductions in crime in the network than lower-centrality criminals.

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 2010 to 2012. We use this edge list to construct a set of co-offending networks. Our dataset encompasses 29,369 networks and includes 108,018, individual offenders.

The minimum network size is 2. The median is also 2. The mean is 4 and the maximum network size is 6,273. There are 438 networks that include 10 or more offenders, and 53 networks that include 100 or more offenders.

For each person, in each network, we calculate two measures of network centrality, eigenvector centrality and degree centrality, and one measure of criminal activity.[6] We then label each person

[6]Degree centrality counts the number of people that an offender is directly linked to (it counts co-offenders) and then divides this number by the total number of people in the offender's network (excluding themselves). Eigenvector centrality

as a highly central person and/or a highly active person if they are above the median within their own network along these dimensions.

3.1 Co-Offender Deaths

We match on birth year and month of death (when applicable) to these data using information from Statistics Sweden's Full Population Register. We also have data on the primary cause of death, which comes from the National Board of Health and Welfare's Cause of Death Register, and hospitalization data from their Inpatient Register.

In our dataset of co-offenders, we observe 679 individuals who died between 2010 and 2012. Table 1 provides more information concerning these deaths. The main cause of death is listed, 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 (255). 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. The mean age at death is 40. 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 5 nights.

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 before their co-offender passes away. The timing of the treatment in our DiDs and event studies would be muddied. Alternatively, crime and conflict could be on the rise. This increase in conflict could affect the probability of dying (being murdered, for example) and affect the future behavior of a deceased offender's peers (through retaliation, for example).

To examine pre-mortem trends in crime, we look at 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 2, we see that the deceased individual's own crime does not display any trends prior to their own death. Despite the lack of a trend in average pre-mortem crime, we choose to exclude the 30 individuals who die from assaults from our main analyses 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. [7]

also takes into account an offender's second-degree links (co-co-offenders), third-degree links, and so on. An offender has a high eigenvector centrality if they have many connections to other well-connected offenders.

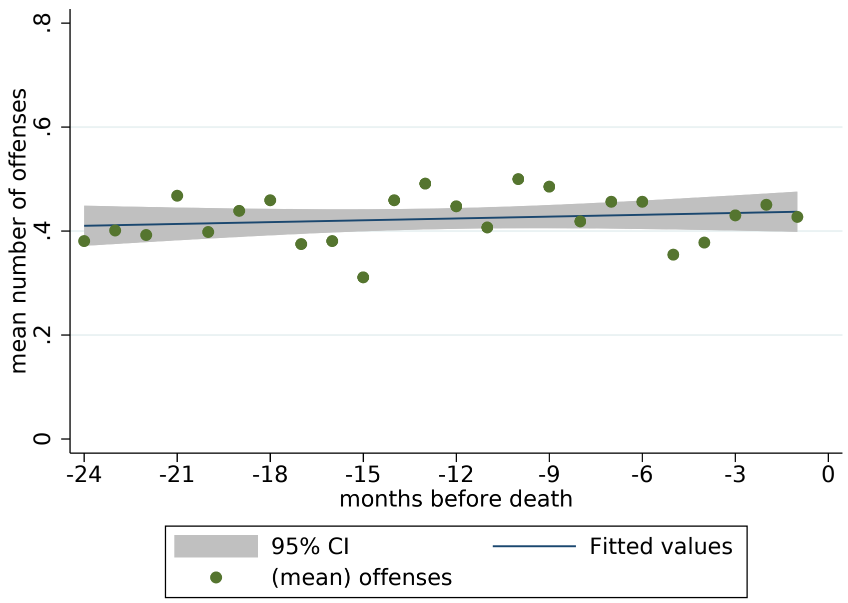
[7] Offenders enter our sample the first time they are suspected of a co-offense during the years 2010 to 2012. Our sample is fixed at the end of 2012 and includes all persons who are suspected of at least one co-offense. New offenders enter each month so that the sample grows (linearly) over time. The 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. In Appendix Figure A1, 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

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

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

Figure 2: 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.

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 match on 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.[8] But we also add them together when we want to 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 then add monthly convictions and prison sentences as additional outcomes. These last two outcome variables are taken from the Convictions Register, which is also maintained by the Swedish National Council for Crime Prevention.

We exclude the 30 offenders who died from assaults during our sample period, 2010-2012. Their peers are excluded from our analysis sample as well. We then drop the remaining 649 people who die during our sample period. Only those who are 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 that died during any given month. We call 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 are shown in Table 2. We see that 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. They have on average 2.5 co-offenders, 3.7 co-co-offenders, and 8 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%.

$t = 1$ and $T - 1$. These are the offenders in our sample who could potentially die in month T.

[8] 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.

Table 2: Descriptive Statistics for Individual-Level Data

	mean	sd	min	p50	max
		A. Outcomes			
Total Offenses	6.006	9.631	1	2	297
Co-Offenses	2.174	2.728	0	1	75
Solo-Offenses	3.832	8.164	0	1	252
Total Co-offenders	3.187	7.733	0	2	999
Convictions No Prison	0.996	1.557	0	0	26
Convictions Prison	0.169	0.564	0	0	12
		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	8.0	24.3	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

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.

3.3 Network-level monthly panel data

We also create a network-level monthly panel dataset, which is constructed using our monthly offender level panel dataset (i.e., we simply re-arrange the same data). Specifically, we take each of the 649 co-offenders who die from something other than assault during the 2010 to 2012 period and build an egocentric network around each one of 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 collapse (by summing) these data into aggregate, egocentric network level data. This gives us a monthly panel of aggregate crime outcomes for all persons belonging to each egocentric network. When constructing these egocentric networks, we lose three pairs of deceased offenders due to network overlap, which leaves us with 643 egocentric networks in which only one offender dies.

Descriptive statistics are shown in Table 3. The minimum network size is 2. The median size is 6 and the largest network includes 328 offenders. On average, these networks commit 100 co-offenses and 321 solo offenses. They receive nearly 63 convictions without a prison sentence and 16 convictions that include a prison sentence; 27 percent of networks experience the death of a high eigenvector centrality offender; 19 percent experience the death of a high degree centrality offender, and 70 percent 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 Degree Centrality	643	0.19	0.39	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

We use co-offender deaths as a source of exogenous variation to estimate individual level spillover effects. We want to 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 of offender i is defined as the loss of 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. For each link distance $l \in \{1, 2, 3\}$, we estimate:

$$Y_{it} = \alpha_i + \beta_t + \sum_{j=-12}^{12} \tau_j \mathbf{1}[\text{time since death} = j] + \epsilon_{it}, \tag{6}$$

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.[9] $\mathbf{1}[\text{time since death} = j]$ 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 and report static DiD specifications as follows:

$$Y_{it} = \alpha_i + \beta_t + \tau D_{it} + \epsilon_{it}, \tag{7}$$

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.

[9] 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 6 are set at that level. In section 4.3, we reestimate spillover effects for those who experience only one unique death.

4.1.1 Identifying assumptions

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

In our dynamic setting, in which treatment can occur during any of the months (except in the first), the main identifying assumption is that the timing of the treatment event is exogenous to the development of the outcome variable after conditioning on individual and time fixed effects. In our specific setting, this means that the timing of co-offender k's death should be conditionally exogenous to offender i's criminal behavior. 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. $Y_{0,it} = \alpha_i + \beta_t + \gamma_{it} + u_{i0}$.

4.1.2 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 3, 4, and 5 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 viability of the post-treatment parallel trends assumption.

One could 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, in Figure 2, we saw that the criminal behavior of those who will die does not trend up or down before their deaths. Furthermore, in Table 1, we saw 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 their 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.

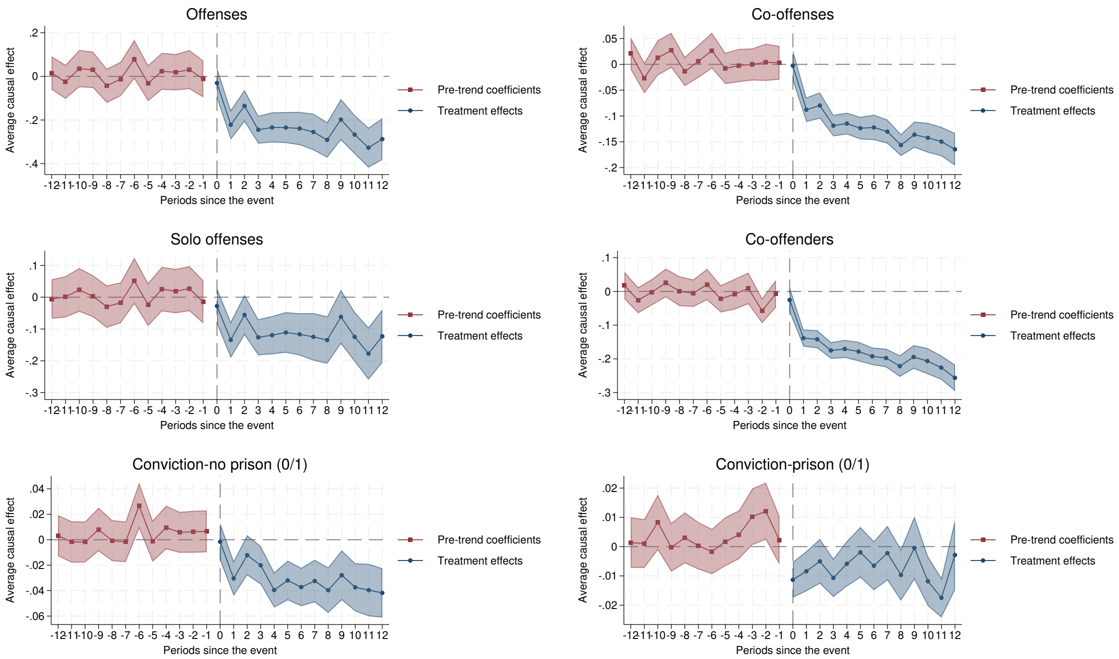
More generally, the DiD estimation strategy is not robust to either unobserved shocks, u_{i0}, that cause the event or treatment and affect subsequent behavior, nor to time varying individual level unobservables, γ_{it}. Both are assumed to be absent in our estimated counterfactual. Our identification 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 study 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.

4.2 Results

We begin by presenting results through a series of event study graphs. Figures 3, 4, and 5 illustrate the impact of one-step, two-step, and three-step away deaths of cooffenders, respectively. Specifically, for each of the four suspects outcomes —number of offenses, cooffenses, solo offenses, and cooffenders— and the two convictions outcomes —whether offender was convicted without a prison sentence (0/1) and whether they were sentenced to prison (0/1)— we present the estimated coefficients from specification 6. The post-treatment coefficients estimates should be interpreted as showing the effects of experiencing a death at time zero, relative to the pre-treatment period.

One-step deaths. Starting with one-step away deaths in Figure 3, we observe no significant pretrends for any of the outcomes–the coefficients on the months prior to the death are small and not statistically significant. The impact of the cooffender's death on total offenses is consistently negative and statistically significant. The effect becomes noticeable one month after the event and persists for the entire 12-month period that we examine, with a slight tendency for the effect to increase in absolute value. Our static DiD estimate reported in Table 4a suggests that in the 12-month period following the death of a cooffender, the number of offenses decreases by 0.277 per month, which amounts to 47% of the pre-treatment mean. Both cooffenses and solo-offenses see a decrease, and there is a reduction of 0.22 in the number of cooffenders. We also see a significant reduction in conviction rates (no prison) of 3.5 percentage points and of 0.9 percentage points of those involving a prison sentence. Given that the incidence of convictions is rather modest, 8.7% and 2.2%, respectively, the effect sizes we estimate are sizeable, amounting to about 40% of the pre-treatment mean.

Figure 3: Impact of one-step away deaths.

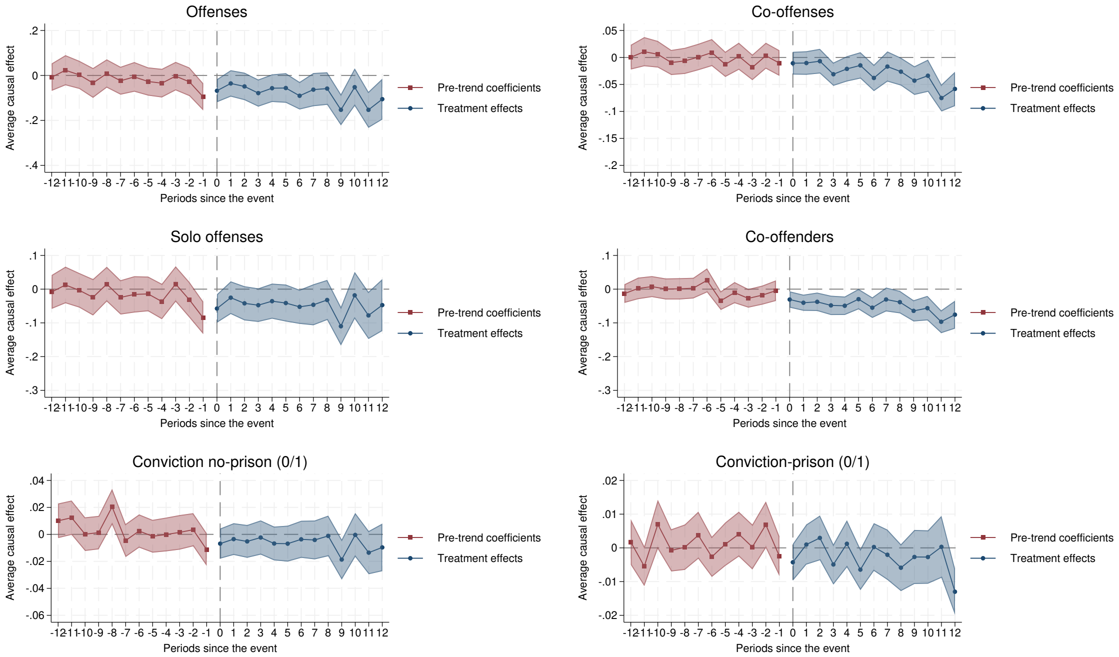


Notes: The figures plot estimates of the dynamic DiD model in equation 6 for one-step away deaths estimated using the Borusyak et al. (2024) two-step imputation method. 5% confidence intervals are shown, using standard errors clustered at the offender i level.

Two-step deaths. We next turn attention to the impact of a death not on a direct cooffender but on a cooffender of a cooffender (co-cooffender). Figure 4 shows a negative but more muted effect on all outcomes compared to the direct effect of a death on a cooffender, as presented earlier. The static DiD estimate shown in Table 4b indicates a statistically significant decrease of the number of offenses committed by the co-cooffender of 0.1, or 14.6% of the pre-treatment mean. Conviction rates (no prison) also decrease by 1.1 percentage points. Note that in the case of this outcome we reject the null hypothesis of no pre-trends.

Three-step deaths. Finally, we examine the impact of a death of an offender on an individual that is three steps away from them in the network, meaning that they have cooffended with a cooffender of one's cooffender. Figure 5 shows still a negative effect for all outcomes, albeit the size of the effects is smaller than those for deaths that are one or two-step away. The static DiD estimate reported in

Figure 4: Impact of two-step away deaths.



Notes: The figures plot estimates of the dynamic DiD model in equation 6 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.

Table 4c implies a statistically significant decrease of the number of offenses by a co-co-cooffender of 0.059, or 7.9% of the pre-treatment mean. Conviction rates (with prison) also show a statistically significant reduction of 0.3 percentage points.

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 criminal network. Notably, these effects extend beyond their direct cooffenders, impacting individuals who are not directly linked to the deceased offender. Furthermore, our findings suggest a decaying pattern in the magnitude of these 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 section 2.3.

4.2.1 Robustness and Placebo Tests

In Table A1, we report various robustness checks. We show that our findings 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) 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 1-step away deaths.

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

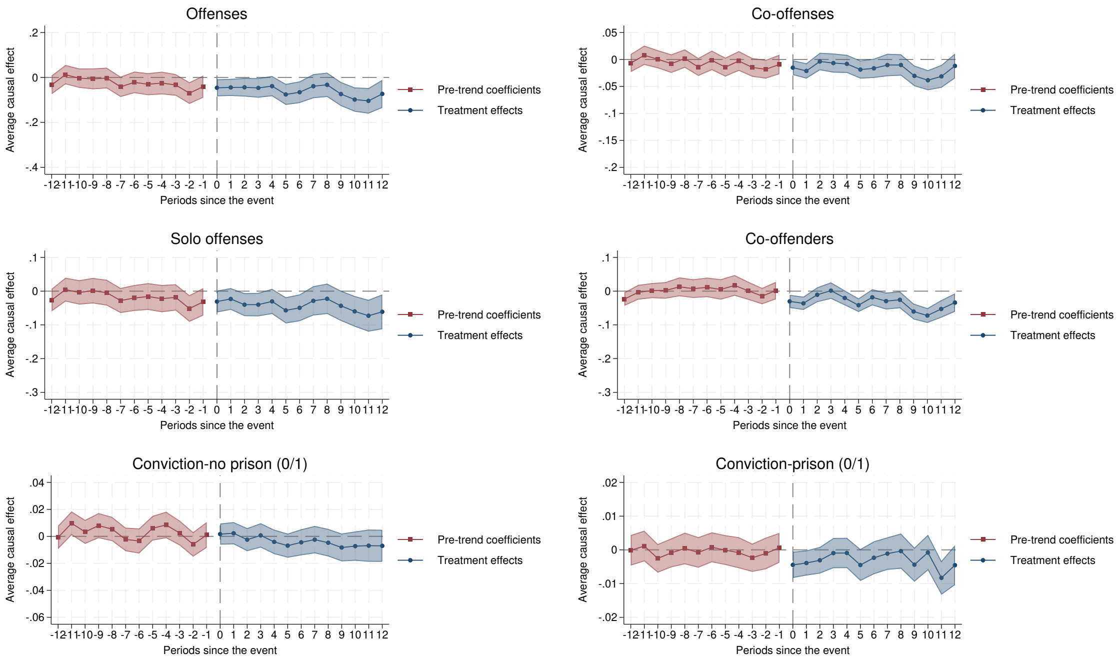
	(1) Offenses	(2) Co-Offenses	(3) Solo-Offenses	(4) Co-Offenders	(5) Conviction No prison	(6) Conviction Prison
DiD	-0.100***	-0.034***	-0.066***	-0.057***	-0.011***	-0.003*
	(0.020)	(0.007)	(0.016)	(0.009)	(0.003)	(0.001)
Observations	3,872,844	3,872,844	3,872,844	3,872,844	3,872,844	3,872,844
number 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

The table report static DiD estimates using Borusyak et al. (2024)'s two-step imputation method.
Standard errors in parentheses clustered on networks; *** p<0.01, ** p<0.05, * p<0.1.

Figure 5: Impact of three-step away deaths.



Notes: The figures plot estimates of the dynamic DiD model in equation 6 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.

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 7) 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 A2, we see that this exercise produces a set of precisely estimated zeros. No iteration produced a larger estimate than our baseline estimates, which provides reassurance that our estimates are uncovering true spillover effects.

4.3 Results Using Single-Death Events

In our sample period, some offenders may be exposed to multiple deaths of co-offenders, co-co-offenders, or co-co-co-offenders. This implies that the effects estimated in the previous section may be influenced by these simultaneous treatments. To address this issue and isolate a cleaner treatment effect of deaths, we now shift our focus to a subset of offenders who have experienced only unique events. These unique events refer to the death of an offender that is either one, two, or three steps away.

Table 5a presents results for one-step away unique deaths. Similar to the previous analysis, we find no statistically significant pretrends, except for co-offenders. After a death occurs, we observe that the permanent removal of a one-step away co-offender leads to a reduction of 0.215 in an offender's total offenses. Looking by component, we see that both, solo and cooffenses witness a decrease, by 0.12 and 0.09, respectively. We also observe a reduction of 3.5 percentage points in conviction rates (no-prison). In the case of removing a two-step away co-offender, offenses decrease by 0.046, which is about 10.6% of the mean (see Table 5b). While this effect is smaller than the one-step away scenario, it still indicates some influence on an offender's behavior. The effect on conviction rates without prison is also smaller (0.9 of a percentage point), while that on convictions with a prison sentence is not statistically significant. Notably, the effect of removing a three-step away co-co-co-offender on both offenses and convictions is essentially zero (see Table 5c). Therefore, we observe a gradual decay of the effect toward zero as we move from considering the impact on one-step away offenders to three-steps away offenders.

Table 5: 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

The table reports DiD estimates for offenders who have experienced only unique events, using the Borusyak et al. (2024) two-step imputation method. * p<0.10, ** p<0.05, *** p<0.01

5 Learning about the Probability of Conviction

Our theoretical model predicts that if a co-offender death 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, offenders will increase their criminal activity.

To explore this prediction, we first need a measure of how often offenders are caught and convicted. While we do not observe how many crimes they actually commit, 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, having a P equal to one means that the offender is always convicted, while having a P equal to zero means that they are never convicted. The sample mean of P is 0.32; 36% of the sample has a P equal to 0, while 10% has a P equal to 1.

In the context of co-offender deaths, the key mechanism 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 even in the future.

We take our sample of one-step away co-offenders who have experienced a co-offender death. We calculate the change in the average P that they experience after the death of a co-offender, $\Delta \bar{P}$. We do this in the manner outlined in the examples in Section 2.2. We split this sample into those with positive and negative values of $\Delta \bar{P}$ and estimate static DiD regressions for each group separately.

In line with our theoretical predictions, we see that there is a larger reduction for those offenders experiencing a positive $\Delta \bar{P}$ (see Panel A in Table 6) than those who experience a negative $\Delta \bar{P}$ (see Panel B in Table 6). These differences are statistically significant and they hold across all outcomes.

Table 6: 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

The table reports DiD estimates of tau in equation 7 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.

* p<0.10, ** p<0.05, *** p<0.01

6 Network-Level Analysis

In the previous two sections, we learned that the death of a co-offender has a crime-reducing effect on the surviving members of their network. The total spillover effect of removing a specific offender i on total offenses (for example) can be calculated as follows:

$$\begin{aligned}\text{total spillover effect from removing offender } i = \text{number of one-step away links of } i \times 0.216 \\ + \text{number of two-step away links of } i \times 0.049,\end{aligned} \tag{8}$$

where we observe the number of links in our data, and where the causal effect of removing a single one- or two-step away link was estimated to be 0.216 and 0.049, respectively (see column (1) in Table 5). These numbers refer to the effect on total suspected offenses (as an illustrative example). In Table 2, we see that the median number of one-step away links is 1 and the mean is 2.5. The median number of two-step away links is 0 and the mean is equal to 3.7. Thus, the total spillover effect from removing one offender is on average equal to 2.5 x 0.216 + 3.7 x 0.049 = 0.72 offenses. This is a non-trivial reduction in crime.

In this section, we argue that policy makers should focus more attention and resources on those offenders who have high potential spillover effects. Removing them will lead to larger reductions in crime than a policy that simply arrests a typical offender. Furthermore, as we shall demonstrate, a policy that removes these "key players" will most likely dominate a strategy of targeting only the most active offenders.

Since the size of the total spillover effect depends on the number of one and two-step away links, it is closely related to two particular and well known measures of network centrality: degree centrality and eigenvector centrality. Degree centrality is the number of one-step away links that an individual has, normalized for network size. Eigenvector centrality is constructed in a way that makes use of both direct and indirect links, and can also be normalized for network size. Thus, unlike degree centrality, eigenvector centrality also makes use of information about the number of two-step away links, as well as links three or more steps away.

Table 7 shows a set of simple correlations calculated using our individual-level dataset. For each offender, we use equation (8) to calculate the total spillover effect they would generate if they were to be removed from their network. Then, we create a set of dichotomous variables equal to one for high values of the total spillover effect, degree centrality, eigenvector centrality, and number of offenses. By "high" we mean that they are above the median value *within their own network*.

In Table 7, we see that both high degree centrality and high eigenvector centrality are strongly correlated with a high total spillover effect. These correlations are two to three times larger than the correlation between a high total spillover effect and committing a high number of offenses. The correlation between high degree centrality and high eigenvector centrality is 0.54.

The main purpose of our network-level analysis is to use these related facts to test a key player policy. Can we predict which offender deaths (removals) will lead to the largest reductions in aggregate crime in a network? Our theoretical model predicts that the death of a high degree centrality

Table 7: Correlations Between Expected Spillover Effects and Measures of Network Centrality and Criminal Activity

	High spillover effect	High degree centrality	High eigenvector centrality	High number offenses
High spillover effect	1.00			
High degree centrality	0.88	1.00		
High eigenvector centrality	0.59	0.54	1.00	
High number offenses	0.31	0.31	0.18	1.00

or eigenvector centrality offender will lead to larger reductions in crime than the death of a typical offender or the death of one of the most active offenders (if they are not well connected). See section 2.3.

6.1 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 and not 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. 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:

$$Y_{n[-i]t} = \alpha_{n[-i]} + \beta_t + \tau D_{n[-i]t} + \epsilon_{n[-i]t}, \tag{9}$$

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; $\alpha_{n[-i]}$ and β_t are network and month-by-year fixed effects, respectively. The parameter τ captures the average treatment effect of a death of a co-offender on network-level spillover effects on the crime of the surviving network members, $Y_{n[-i]t}$, net of network- and time-specific 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 centrality co-offender. Does the death of a high centrality offender lead to a greater reduction in crime than the death of a low centrality individual?

We then run our key player analysis that examines the effect of network centrality on total crime at the network level, Y_{nt}. Total crime includes both the spillover effect and the direct effect from removing offender i's own crime. To do this, we include the deceased offender in the network data and estimate:

$$Y_{nt} = \alpha_n + \beta_t + \tau D_{nt} + \epsilon_{nt}. \tag{10}$$

6.2 Results: The Effect of Network Centrality on Aggregate Spillovers

Our network-level analysis includes 643 egocentric networks in which the focal person is a deceased co-offender. Each network is comprised of all one-step, two-step, and three-step away co-offenders connected to a unique offender death. We follow each network for 36 months and compare the aggregate monthly outcome before and after a co-offender death, after netting out network and time fixed effects, and after excluding the crime of the deceased co-offender. This exercise measures the total network level spillover effect and assesses how this effect changes with respect to the network centrality of the deceased offender.

In Table 8, we present estimates of the average network-level spillover effect 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.

The average treatment effect for total offenses is a statistically significant reduction of 1.12 offenses. This amounts to a 9% reduction relative to the pre-treatment mean of 12.37. Spillover effects on crime range from -8% for solo-offenses to -17% for convictions that include a prison sentence. The number of co-offenders is reduced by 24%. Note also that we report the p-value from our pre-trends test for each DiD event study regression. We find no evidence of pre-trends and/or anticipation effects.

Our centrality exercise tests for heterogeneous effects. These are shown in columns (2) - (4) and (6) - (8) in Table 8. For each of our six outcomes the death (and subsequent permanent removal) of a high degree centrality offender leads to a significantly higher reduction in crime compared to the death and removal of a low degree centrality offender. Removing a high degree centrality offender generates the highest absolute decrease in crime for all six of our crime outcome variables.

If we rank our 3 measures, then high degree centrality always outperforms high eigenvector centrality, which in turn outperforms the removal of the most active offenders. Eigenvector centrality, however, does not help us to identify aggregate spillovers when we are examining more serious crimes, i.e. convictions that include a prison sentence. In Panel F of Table 8, we see that what matters for serious convictions is the removal of a high degree and/or high offending individual.

Table 8: Network Level Spillover Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment Effect		Eigenvector Centrality	Degree Centrality	Offense Rate		Eigenvector Centrality	Degree Centrality	Offense Rate
		Panel A: Total Offenses				Panel B: Solo-Offenses		
Average	-1.116**				-0.774**			
	(0.514)				(0.347)			
Low		-0.845	-0.762	-0.515		-0.599*	-0.559	-0.314
		(0.535)	(0.540)	(0.724)		(0.359)	(0.372)	(0.487)
High		-1.855***	-2.969***	-1.317***		-1.253***	-1.902***	-0.929***
		(0.630)	(0.822)	(0.511)		(0.452)	(0.588)	(0.350)
p-value no pre-trends	0.753				0.442			
p-value for equality		0.058	0.006	0.174		0.102	0.027	0.135
Pre-treatment mean	12.37				9.363			
Relative effect size	-9%				-8%			
		Panel C: Co-Offenses				Panel D: Co-Offenders		
Average	-0.341*				-0.901***			
	(0.195)				(0.282)			
Low		-0.246	-0.203	-0.200		-0.494*	-0.571**	-0.565
		(0.201)	(0.197)	(0.261)		(0.285)	(0.283)	(0.357)
High		-0.602***	-1.067***	-0.389***		-2.013***	-2.636***	-1.014***
		(0.230)	(0.285)	(0.194)		(0.392)	(0.458)	(0.291)
p-value no pre-trends	0.949				0.887			
p-value for equality		0.052	0.000	0.353		0.000	0.000	0.132
pre-treatment mean	3.004				3.807			
Relative effect size	-11%				-24%			

Table 8: Network Level Spillover Analysis, ... continued

Treatment Effect	(1)	(2) Eigenvector Centrality	(3) Degree Centrality	(4) Offense Rate	(5)	(6) Eigenvector Centrality	(7) Degree Centrality	(8) Offense Rate
	Panel E: Convictions, No prison				Panel F: Convictions, Prison			
Average	-0.202***				-0.0795***			
	(0.0633)				(0.0211)			
Low		-0.144**	-0.163**	-0.116		-0.0848***	-0.0678***	-0.0408
		(0.0681)	(0.0674)	(0.0707)		(0.0221)	(0.0228)	(0.0264)
High		-0.361***	-0.407***	-0.231***		-0.0652**	-0.141***	-0.0926***
		(0.0768)	(0.110)	(0.0702)		(0.0315)	(0.0328)	(0.0232)
p-value no pre-trends	0.219				0.982			
p-value for equality		0.005	0.034	0.106		0.535	0.042	0.057
Pre-treatment mean	1.812				0.460			
Relative effect size	-11%				-17%			
Observations	23,148	23,148	23,148	23,148	23,148	23,148	23,148	23,148
Number of networks	643	643	643	643	643	643	643	643

The table report static DiD estimates using Borusyak et al. (2024)'s two-step imputation method. Standard errors in parentheses clustered on networks.
*** p<0.01, ** p<0.05, * p<0.1

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

Next we perform our key player exercise. To do this, we repeat the above exercise – but include the pre-mortem crimes committed by the deceased co-offender. This allows us to measure the reduction in aggregate network level crime that arises after the death of a co-offender. This measure includes the indirect spillover effect (measured above) and the direct effect of removing the crime of the deceased co-offender. We then analyze how the total reduction in crime is affected by the centrality of the deceased co-offender and by the level of their criminal activity. What type of offender should we focus our resources on in order to achieve the largest reduction in crime, a more central offender or a more active offender?

Panel A of Table 9 reports an average effect on total (suspected) offenses of -1.62 (0.524), which is equivalent to a reduction in crime of 13% of the pre-treatment mean. Co-offender deaths reduce overall crime in our networks. Average effects range from -12% for solo-offenses to as much as -18% for convictions that include a prison sentence. The number of unique co-offenders in each network drops by 27% (on average).

These large average effects hide substantial heterogeneity by offender centrality and criminal activity. In columns (2) - (4) and (6) - (8), we see that the death of a high eigenvector or degree centrality offender leads to much larger absolute reductions in crime than does the death of a low centrality offender. For total offenses (Panel A), the absolute reduction in crime increases from -1.62 crime to -3.88 crimes after the death of a high degree offender.

As expected, the death of a highly active offender also leads to larger than average reductions in crime. The main takeaway from Table 9, however, is that the death of a high degree centrality offender systematically leads to higher absolute reductions in crime than the death of a high crime offender. This we argue is an important result – a proof of concept – that measures of network centrality can be used to help identify who the police should focus more attention on. High degree centrality individuals are the key players in our context. A high degree indicates that they are active criminals who also generate large spillover effects.

Table 9: Key Player Analysis

Treatment Effect	(1)	(2) Eigenvector Centrality	(3) Degree Centrality	(4) Offense Rate	(5)	(6) Eigenvector Centrality	(7) Degree Centrality	(8) Offense Rate
		Panel A: Offenses				Panel B: Solo-Offenses		
Average	-1.619***				-1.147***			
	(0.524)				(0.355)			
Low		-1.305**	-1.189**	-0.976*		-0.938**	-0.873**	-0.671*
		(0.545)	(0.549)	(0.572)		(0.367)	(0.380)	(0.394)
High		-2.475***	-3.876***	-2.509***		-1.717***	-2.584***	-1.806***
		(0.641)	(0.834)	(0.599)		(0.466)	(0.602)	(0.415)
p-value no pre-trends	0.845				0.554			
p-value for equality		0.032	0.001	0.004		0.060	0.006	0.004
Pre-treatment mean	12.81				9.712			
Relative effect size	-13%				-12%			
		Panel C: Co-Offenses				Panel D: Co-Offenders		
Average	-0.472**				-1.064***			
	(0.199)				(0.284)			
Low		-0.367*	-0.316	-0.305		-0.632**	-0.707**	-0.808***
		(0.205)	(0.200)	(0.212)		(0.286)	(0.285)	(0.305)
High		-0.758***	-1.292***	-0.703***		-2.242***	-2.935***	-1.418***
		(0.233)	(0.287)	(0.221)		(0.395)	(0.457)	(0.326)
p-value no pre-trends	0.982				0.885			
p-value for equality		0.033	0.000	0.025		0.000	0.000	0.030
Pre-treatment mean	3.099				3.910			
Relative effect size	-15%				-27%			

Table 9: Key Player Analysis, ... continued

Treatment Effect	(1)	(2) Eigenvector Centrality	(3) Degree Centrality	(4) Offense Rate	(5)	(6) Eigenvector Centrality	(7) Degree Centrality	(8) Offense Rate
	Panel E: Convictions, No Prison				Panel F: Convictions, Prison			
Average	-0.243***				-0.0828***			
	(0.0652)				(0.0212)			
Low		-0.180***	-0.196***	-0.118		-0.0872***	-0.0696***	-0.0361
		(0.0699)	(0.0691)	(0.0723)		(0.0221)	(0.0229)	(0.0265)
High		-0.414***	-0.492***	-0.285***		-0.0708**	-0.152***	-0.0985***
		(0.0793)	(0.112)	(0.0721)		(0.0316)	(0.0334)	(0.0233)
p-value no pre-trends	0.195				0.979			
p-value for equality		0.003	0.011	0.021		0.604	0.025	0.023
Pre-treatment mean	1.873				0.473			
Relative effect size	-13%				-18%			
Observations	23,148	23,148	23,148	23,148	23,148	23,148	23,148	23,148
Number of networks	643	643	643	643	643	643	643	643

The table report static DiD estimates using Borusyak et al. (2024)'s two-step imputation method. Standard errors in parentheses clustered on networks.
*** p<0.01, ** p<0.05, * p<0.1

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.

First of all, the loss of a co-offender lowers overall crime among an offender's peers 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 contradicts 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, it is plausible that forming new co-offending relationships takes time, incurs high costs, and substantial risks.

Our findings provide evidence that the concept of strategic complementarities encompasses multiple mechanisms. The loss of a co-offender lowers both co-offenses and solo-offenses among surviving offenders; with the largest impact being on co-offenses. The reduction in solo-offenses can be attributed to less tangible or less technical forms of complementarities, such as the loss of information about criminal opportunities, the absence of a role model, or changes in the social norm of a group.

The larger decrease in co-offenses compared to solo-offenses suggests that some offenders either need or prefer the presence of another person to commit certain crimes. Therefore, the absence of a potential co-offender restricts the execution of crimes that necessitate multiple individuals. The need or desire 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, network connectivity and network centrality are crucial properties of co-offending networks that facilitate 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 role of social interactions and networks in 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 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 support in favor of exit strategies and relocation policies that permanently remove offenders from their co-offending networks.

Our results show that removing a more central co-offender generates larger spillover effects and a larger absolute reductions in crime than the removal of a less central co-offender. The removal of highly central individual also 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 use measures of network centrality when choosing which offenders to target.

Our study introduces a new hypothesis on how beliefs about the cost of crime are formed, highlighting the impact of reduced future information availability due to the loss of a co-offender. Our empirical findings show 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 help lower crime.

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Appendix

Figure A1: The Share of Offenders that Die Each Month

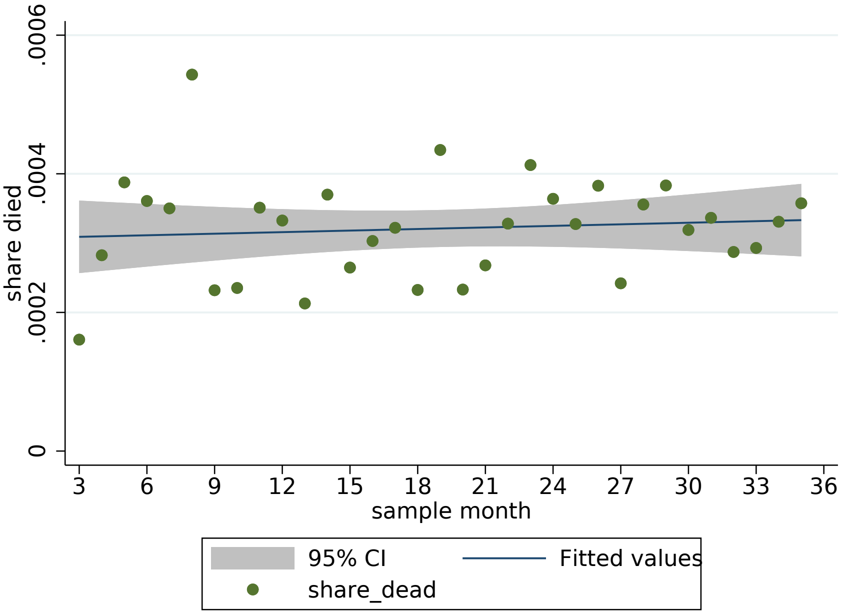

Table A1: Robustness checks: 1-Step Away Deaths

	(1) Offenses	(2) Co-Offenses	(3) Solo-Offenses	(4) Co-Offenders	(5) Conviction No prison	(6) Conviction Prison
Panel A. Excluding deaths of under 18 and above 65						
D	-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						
D	-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. Excluding deaths preceded by long hospitalizations						
D	-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: The table reports DiD estimates of tau in equation 7 for one-step away deaths using the Borusyak et al. (2024)'s two-step imputation method. The first panel exlcudes deaths of under 18 and above 65, the second panel excludes deaths related to narcotics and alcohol, and the third panel excludes deaths preceded by long hospitalizations (more than 5 days).

Table A2: Placebo: 1-Step Away Deaths

	(1) Offenses	(2) Co-Offenses	(3) Solo-Offenses	(4) Co-Offenders	(5) Conviction No prison	(6) Conviction Prison
Panel A. Actual						
D	-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 7) and report summary statistics of the obtained coefficients.