Criminal Networks: Who is the Key Player?∗†

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Abstract

We propose a new methodology to test who the key player is in criminal networks, i.e. the delinquent who, once removed from the network, generates the highest possible reduction in aggregate delinquency level. Using data on adolescent delinquents in the United States, we then provide new results regarding the identification of peer effects and determine the key player in each delinquent network. We show that, compared to a policy that removes the most active delinquents from the network, a key player policy engenders a crime reduction that can be as large as 35 percent. We discuss how to implement the key-player policy in the real world, primarily within criminal networks, but also within financial, R&D, development, political and tax-evasion networks.

Key words: Crime, Katz-Bonacich centrality, estimation of peer effects, crime policies.

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1 Introduction

There are 2.3 million people behind bars at any one time in the United States, and that number continues to grow. It is the highest level of incarceration per capita in the world. Moreover, since the crime explosion of the 1960s, the prison population in the United States has multiplied fivefold, to one prisoner for every hundred adults — a rate unprecedented in American history and unmatched anywhere in the world. However, in spite of a continuously falling crime rate, the prisoner head count continues to rise, and poor people as well as minorities still bear the brunt of both crime and punishment.

One possible way to reduce crime is to detect, apprehend, convict, and punish criminals. This is what has been done in the United States and all of these actions cost money, currently about $200 billion per year nationwide. For example, in California, even if this “brute force” policy has partly worked (the rate of every major crime category is now less than half of what it was 20 years ago), the cost of this policy has been tremendous. Consider, for example, that the cost of the justice system is higher than the cost of education.

In his recent book published in 2009, Mark Kleiman argues that simply locking up more people for lengthier terms is no longer a workable crime-control strategy. But, says Kleiman, there has been a revolution in controlling crime by means other than brute-force incarceration: substituting swiftness and certainty of punishment for randomized severity, concentrating enforcement resources rather than dispersing them, communicating specific threats of punishment to specific offenders, and enforcing probation and parole conditions to make community corrections a genuine alternative to incarceration. As Kleiman shows, “zero tolerance” is nonsense: there are always more offenses than there is punishment capacity.

Is there an alternative to brute force? In this paper, we argue that concentrating efforts by targeting “key criminals”, i.e. criminals who once removed generate the highest possible reduction in aggregate crime level in a network, can have large effects on crime because of the snow-ball effects or “social multipliers” at work (see, in particular, Kleiman, 2009; Glaeser et al., 1996; Verdier and Zenou, 2004; Calvó-Armengol and Zenou, 2004). That is, as the fraction of individuals participating in a criminal behavior increases, the impact on others is multiplied through social networks. Thus, criminal behaviors can be magnified, and interventions can become more effective. Furthermore, the impact of social networks may be particularly important for adolescents because this developmental period overlaps with the initiation and continuation of many risky, unhealthy, and delinquent behaviors and is a period of maximal response to peer pressure (Thornberry et al., 2003; Warr, 2002).

It is indeed well-established that delinquency is, to some extent, a group phenomenon, and that the sources of crime and delinquency are located in the intimate social networks of individuals (see

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1 See Cook and Ludwig (2010) and the references therein.
2 For example, the “Three Strikes” law passed in California in 1994 mandates extremely long prison terms (between 29 years and life) for anyone previously convicted in two serious or violent felonies (including residential burglary) when convicted of a third felony, even for something as minor as petty theft.
3 In the economic crime literature (Becker, 1968; Garoupa, 1997; Polinsky and Shavell, 2000), punishment is seen as an effective tool for reducing crime.
Delinquents often have friends who have themselves committed several offences, and social ties among delinquents are seen as a means whereby individuals exert an influence over one another to commit crimes. In fact, not only friends, but also the structure of social networks, matters in explaining an individual’s own delinquent behavior. This suggests that the underlying structural properties of friendship networks must be taken into account to better understand the impact of peer influence on delinquent behavior and address adequate and novel delinquency-reducing policies.

The aim of this paper is to investigate the importance of the key player in criminal networks by proposing a methodology that helps detect the key player in the real world. For that, we use the theoretical model of Ballester et al. (2006) to identify the key player. We then test this model on the data. In order to determine the key player, we need to estimate the intensity of interactions between criminals in each network. Most of the network models in the literature use the identification approach proposed by Bramoullé et al. (2009), which assumes that the adjacency matrix (or sociomatrix) is row-normalized (the so-called local-average model). With a row-normalized adjacency matrix, a criminal’s effort level depends on the average effort level of his/her criminal friends (Patacchini and Zenou, 2012). However, key-player policies make more sense in the context of the local-aggregate model developed by Ballester et al. (2006) with a non-row-normalized adjacency matrix, where it is the sum of friends’ efforts that affects own effort. This is because, once we remove a delinquent from a network, there are snow-ball or multiplier effects on other criminals. In this paper, we provide a new identification strategy for the local-aggregate model which is based on the variation of the row sum of the adjacency matrix. We show that the identification condition for the local-aggregate model is weaker than that for the local-average model developed by Bramoullé et al. (2009). We also give some examples of networks for which the local-aggregate model can be identified while the local-average model cannot be.

Using the AddHealth data of adolescents in the United States, we then determine who is the key player in each of 150 networks. We find that the key player is not necessarily the most active criminal in the network. We also find that it is not straightforward to determine which delinquent should be removed from a network by only observing his or her criminal activities or position in the network. Compared to other criminals, the key players are less likely to be a female, are less religious, belong to families whose parents are less educated and have the perception of being more socially excluded. They also feel that their parents care less about them, are more likely to come from single-parent families and have more troubles getting along with their teachers.

We finally discuss the policy implications of our results. First, we develop a qualitative approach.

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5 This idea was also used by Glaeser et al. (1996) in their pioneering study on crime and social interactions. These kinds of effects will not be present in the local average model because, in this model, to affect the behavior of each individual, one needs to change the social norm of all individuals in the network. While it is true that many papers, which typically have no micro-founded model, interpret peer effects as the desire to conform to a social norm and estimate a local average model (e.g., Lin, 2010; Bifulco et al., 2011; Boucher et al., 2014), others, which have a theoretical model, use a local aggregate formulation for peer effects (e.g., Glaeser et al., 1996; Christakis and Fowler, 2007; Calvo-Armengol et al., 2009). The identification conditions for network models with local aggregates have not been studied before.

6 Many theoretical models in the network literature use a local aggregate approach. Our results will be useful in identifying these types of models e.g., Belhaj and Derojan (2012), Zhou and Chen (2012), Bramoullé et al. (2014), etc.
using simulations to evaluate the cost and benefit of the key-player policy. We show that targeting the most active criminals is less effective than the key-player policy. We show that, for small networks, crime reduction after the implementation of the key-player policy can be as high as 35 percent. Second, our key-player policy can be directly applied to reduce crime in the real world when criminal network data are available (we provide a selective list of such data). In fact, some similar policies aiming at reducing crime have already been implemented in the United States but without the analytical tools of the key-player policy. Finally, we show that we can use our methodology to determine the key player in other types of networks and activities, where network data are easier to obtain. This is particularly true for financial networks, R&D networks, networks in developing countries, political networks and tax-evasion networks.

The rest of the paper unfolds as follows. In the next section, we discuss the related literature and explain our contribution. The theory is exposed in Section 3. Our data are described in Section 4. In Section 5, the identification of the econometric network model is discussed while the estimation and empirical results of the impact of peer effects on crime are provided. Section 6 characterizes the key players. In Section 7, we discuss the implications of the key-player policy. Finally, Section 8 concludes.

2 Related literatures

Our paper lies at the intersection of different literatures. We would like to expose them in order to highlight our contribution.

Empirical studies of peer effects in crime There is a growing body of empirical literature suggesting that peer effects are very strong in criminal decisions. Ludwig et al. (2001) and Kling et al. (2005) study the relocation of families from high- to low-poverty neighborhoods using data from the Moving to Opportunity (MTO) experiment. They find that this policy reduces juvenile arrests for violent offenses by 30 to 50 percent, relative to a control group. This also suggests very strong social interactions in crime behaviors. Patacchini and Zenou (2012) find that peer effects in crime are strong, especially for petty crimes. Bayer et al. (2009) consider the influence that juvenile offenders serving time in the same correctional facility have on each other’s subsequent criminal behavior. They also find strong evidence of learning effects in criminal activities since exposure to peers with a history of committing a particular crime increases the probability that an individual who has already committed the same type of crime recidivates that crime.

Our contribution here is to structurally estimate a network model and to propose a way to identify the key player in criminal networks. This paper is the first to present an empirical implementation of the key player policy, which is grounded on a precise behavioral foundation.

Econometrics of networks The literature on identification and estimation of social network models has progressed significantly recently (see Blume et al., 2011 and Durlauf and Ioannides, 2010, for recent surveys). In his seminal work, Manski (1993) introduces a linear-in-means social interaction model with endogenous effects, contextual effects, and correlated effects. Manski shows that the linear-in-means specification suffers from the “reflection problem” and the different social
interaction effects cannot be separately identified. Bramoullé et al. (2009) generalize Manski’s linear-in-means model to a general local-average social network model, whereas the endogenous effect is represented by the average outcome of the peers. They provide some general conditions for the identification of the local-average model (i.e. when the adjacency matrix is row-normalized) using an indirect connection’s characteristics as an instrument for the endogenous effect.

Our contribution to this literature is to go further by first providing a micro-foundation for the local-aggregate model and then providing an identification condition for the local-aggregate model (i.e. when the adjacency matrix is not row-normalized). We show that, in this case, the identification condition is weaker than for the local-average model. We provide some examples of networks where the local-aggregate model can be identified while the local-average model cannot be.

**The key-player problem** The problem of identifying key players in a network is an old one, at least in the sociological literature. Indeed, one of the focuses of this literature is to propose different measures of network centralities and to assert the descriptive and/or prescriptive suitability of each of these measures to different situations (see, in particular, Wasserman and Faust, 1994). Borgatti (2003, 2006) was among the first researchers to really investigate the issue of key players, which is based on explicitly measuring the contribution of a set of actors to the cohesion of a network. The basic strategy is to take any network property, such as density or maximum flow, and derive a centrality measure by deleting nodes and measuring the change in the network property. Borgatti measures the amount of reduction in cohesiveness of the network that would occur if some nodes were not present. Ballester et al. (2006, 2010) were the first to define the key-player problem in terms of behavior of agents so that total activity is measured as the sum of efforts of all agents at a Nash equilibrium.

To the best of our knowledge, this is the first paper that structurally estimates the key player for real-world networks and propose a new methodology on how to estimate it. We also provide concrete recommendations on how to implement the key player policy in the real world, primarily from criminal networks but also for financial, R&D, development, political and tax-evasion networks.

3 Theoretical framework

3.1 Model and Nash equilibrium

Borrowing from Ballester et al. (2006, 2010), we develop a network model of peer effects where the network reflects the collection of active bilateral influences.

**Network** \( N = \{1, \ldots, n\} \) is a finite set of agents in a connected network \( g \equiv g_N \). We keep track of social connections in a delinquency network \( g \) through its adjacency matrix \( G = [g_{ij}] \), where \( g_{ij} = 1 \) if \( i \) nominates \( j \) (\( j \neq i \)) as \( i \)'s friend and \( g_{ij} = 0 \), otherwise. We set \( g_{ii} = 0 \). For the ease of the presentation, we focus on directed networks so that \( G \) can be asymmetric. For each network \( g \) with adjacency matrix \( G = [g_{ij}] \), the \( k \)th power of \( G \) given by \( G^k = G \times \cdots \times G \) keeps track of

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7 Lee (2007) considers a model with multiple networks where an agent is equally influenced by all the other agents in the same network. Lee’s social interaction model is identifiable only if there is variation in network size in the sample. The identification, however, can be weak if all of networks are large.

8 All our theoretical results also hold under undirected networks since the (a)symmetry of the adjacency matrix \( G \) does not play any role in the proof of our theoretical results.
direct and indirect connections in $g$. More precisely, the $(i, j)$th cell of $G_k^e$ gives the number of paths of length $k$ in $g$ from $i$ to $j$. In particular, $G^0 = I$. Note that, by definition, a path between $i$ and $j$ needs not follow the shortest possible route between those agents. For instance, if $g_{ij} = g_{ji} = 1$, the sequence $i \rightarrow j \rightarrow i \rightarrow j$ constitutes a path of length three in $g$ from $i$ to $j$.

**Definition 1** Given a vector $u \in \mathbb{R}_+^n$, and $\phi \geq 0$ a small enough scalar, the vector of Katz-Bonacich centralities of parameter $\phi$ in network $g$ is defined as:

$$b_u(g, \phi) = (I - \phi G)^{-1} u = \sum_{p=0}^{\infty} \phi^p G^p u.$$  \hfill (1)

In words, the Katz-Bonacich centrality of node $i$ counts the total number of walks in $g$ starting from $i$ and weighted by a discount factor $\phi^p$, which decreases with the distance to node $i$.

**Preferences** Delinquents in network $g$ decide how much effort to exert. We denote by $y_i$ the delinquency effort level of delinquent $i$ in network $g$ and by $y = (y_1, ..., y_n)'$ the population delinquency profile in network $g$. Each agent $i$ selects an effort $y_i \geq 0$, and obtains a payoff $u_i(y, g)$ that depends on the effort profile $y$ and on the underlying network $g$, in the following way:

$$u_i(y, g) = (\pi_i + \xi + \epsilon_i) y_i - \frac{1}{\pi} y_i \cdot f \cdot y_i + \phi \sum_{j=1}^{n} g_{ij} y_i y_j$$

where $\phi > 0$. This utility has a standard cost/benefit structure (as in Becker, 1968). The cost of being caught is captured by the probability of being caught $0 < p < 1$, the fine $f \cdot y_i$, which increases with own effort $y_i$, and the severity of the punishment increases with one’s involvement in crime. Also, individuals have a direct cost of committing crime equal to $\frac{1}{\pi} y_i^2$, which is also increasing in own crime effort $y_i$. The proceeds from crime are given by $(\pi_i + \xi + \epsilon_i) y_i$ and are increasing in own effort $y_i$. $\pi_i$ denotes the **exogenous heterogeneity** that captures the observable characteristics of individual $i$ (e.g. sex, race, age, parental education) and the observable **average** characteristics of individual $i$’s best friends, i.e. average level of parental education of $i$’s friends, etc. (**contextual effects**). To be more precise, $\pi_i$ can be written as:

$$\pi_i = \sum_{m=1}^{M} \beta_{1m} x_i^m + \frac{1}{\pi} \sum_{m=1}^{M} \beta_{2m} \sum_{j=1}^{n} g_{ij} x_j^m$$

where $x_i^m$ belongs to a set of $M$ variables accounting for observable differences in individual, neighborhood and school characteristics of individual $i$. $\beta_{1m}, \beta_{2m}$ are parameters, and $\pi = \sum_{j=1}^{n} g_{ij}$ is the number of friends of individual $i$. $\xi$ denotes the the unobservable network characteristics, e.g., the prosperous level of the neighborhood/network $g$ (i.e. more prosperous neighborhoods lead to higher proceeds from crime) and $\epsilon_i$ is an error term, which captures other uncertainty in the proceeds from crime. Both $\xi$ and $\epsilon_i$ are observed by the delinquents (when choosing effort level) but not by the researcher.

Compared to the standard crime model (Becker, 1968), the new element in this utility function is
the last term $\phi \sum_{j=1}^n g_{ij}y_iy_j$, which reflects the influence of friends’ behavior on own action. Indeed, criminals benefit from having criminal mates. This benefit may take the form of know-how sharing about delinquent behavior between individuals that know each other. We assume that the higher the criminal connections to a criminal and/or the higher the involvement in criminal activities of these connections, the higher is the marginal utility of own crime effort. The idea is as follows.

There is no formal way of learning to become a criminal, no proper “school” providing an organized transmission of the objective skills needed to undertake successful criminal activities. Given this lack of formal institutional arrangement, we believe that the most natural and efficient way to learn to commit crime is through the interaction with other criminals. Delinquents learn from other criminals belonging to the same network how to commit crime in a more efficient way by sharing the know-how about the “technology” of crime.

To summarize, the utility function can be written as:

$$u_i(y, g) = (\pi_i + \eta + \epsilon_i)y_i - \frac{1}{2}y_i^2 + \phi \sum_{j=1}^n g_{ij}y_iy_j,$$

where $\eta = \xi - pf$. Note that the utility (2) is concave in own decisions, and displays decreasing marginal returns in own effort levels.

Observe that the utility given by (2) corresponds to the so-called local-aggregate model where it is the sum of active friends that positively affects own utility. There is another model proposed by Patacchini and Zenou (2012), called the local-average model, where deviation from the average effort of active friends negatively affects own utility. Using the same data as in the present paper (AddHealth data), Liu et al. (2013) test the local-aggregate model against the local-average model. They show that, for crime, the local-aggregate model fits this data set better and that is why we adopt this model here.

At equilibrium, each agent maximizes his/her utility (2) and the best-reply function, for each $i = 1, \ldots, n$, is given by:

$$y_i = \phi \sum_{j=1}^n g_{ij}y_j + \pi_i + \eta + \epsilon_i,$$

where $\pi_i$ is defined by (3). Denote by $\mu_1(G)$ the spectral radius of $G$ and by $\alpha_i \equiv \pi_i + \eta + \epsilon_i$, with the corresponding non-negative $n$-dimensional vector $\alpha$. Ballester et al. (2006, 2010) and Calvó-Armengol et al. (2009) have characterized the Nash equilibrium of the game where agents choose their effort level $y_i \geq 0$ simultaneously and shown that, if $\mu_1(G) < 1$, the peer effect game with payoffs (2) has a unique Nash equilibrium in pure strategies given by:

$$y^* \equiv y^*(g) = b_\alpha (g, \phi).$$

This means that the Katz-Bonacich centrality is the right network index to account for equilib-

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Sutherland (1947) and Akers (1998) expressly argue that criminal behavior is learned from others in the same way that all human behavior is learned. Indeed, young people may be influenced by their peers in all categories of behavior - music, speech, dress, sports, and delinquency.
rium behavior when the utility function is linear-quadratic. Observe that

\[ b_\alpha(g, \phi) = (I - \phi G)^{-1} \alpha = \sum_{p=0}^{\infty} \phi^p G^p \alpha \]  

where \( \alpha = \pi + \eta l_n + \epsilon \) and \( l_n \) is an \( n \)-dimensional vector of ones. To simplify notation, we drop the subscript \( \alpha \) in \( b_\alpha(g, \phi) \) whenever there is no ambiguity. Let \( b_i(g, \phi) \) be the \( i \)th entry of \( b(g, \phi) \).

From (6), we have, for each individual \( i \), \( y_i^* = b_i(g, \phi) \). From (5), it is easy to show that the equilibrium utility is equal to:

\[ u_i(y^*, g) = \alpha_i y_i^* - \frac{1}{2} \eta_i y_i^2 + \phi \sum_{j=1}^{n} g_{ij} y_i^* y_j = \frac{1}{2} y_i^2 = \frac{1}{2} [b_i(g, \phi)]^2. \]  

### 3.2 Finding the key player

In the context of the model above, Ballester et al. (2006, 2010) have studied the “key player” policy, which consists of finding the key player, i.e. the delinquent who, once removed from the network, generates the highest possible reduction in aggregate delinquency level. They assume that, once a person is removed from the network, the links of the remaining players do not change.

In Appendix A.1, following Ballester and Zenou (2014), we show that the key player is defined by the intercentrality measure \( d_i(g, \phi) \) of delinquent \( i \) (see (17)). This formula highlights the fact that when a delinquent is removed from a network, two effects are at work. The first one is the contextual effect, which is due to the change in \( \alpha \) after the removal of a delinquent while the network \( g \) remains unchanged. The second effect is the network effect, which captures the change in the network structure when a delinquent is removed. More generally, the intercentrality measure \( d_i(g, \phi) \) of delinquent \( i \) accounts both for one’s exposure to the rest of the group and for one’s contribution to every other exposure. A player \( i^* \) is the key player if and only if \( i^* \) is a delinquent with the highest intercentrality in \( g \), that is, \( d_{i^*}(g, \phi) \geq d_i(g, \phi) \), for all \( i = 1, ..., n \) (Ballester et al. 2006, 2010; Ballester and Zenou, 2014). Observe that this result is true for both undirected networks (symmetric adjacency matrix) and directed networks (asymmetric adjacency matrix). It is also true for adjacency matrices with weights (i.e. values different than 0 and 1) and self-loops (delinquents have a link with themselves).

In Appendix A.2, we develop a dynamic model where both network formation and effort decisions take place. This allows us to extend the key player policy so that, when someone is removed from the network, the other delinquents can create new links with other delinquents. Because, in our dataset, we have network information at one point in time only, we mainly develop this dynamic network formation model as a robustness check exercise to see how well our static model performs. We will use both models in our simulations of the key player policy.

In the following sections, we present the empirical implementation of the key player policy using networks of juvenile delinquents in US schools as a case study. For that, we will first describe the data, then expose the econometric methodologies and finally comment on the empirical results.
4 Data

Our analysis is made possible by the use of a unique database on friendship networks from the National Longitudinal Survey of Adolescent Health (AddHealth). The AddHealth database has been designed to study the impact of the social environment (i.e. friends, family, neighborhood and school) on adolescents’ behavior in the United States by collecting data on students in grades 7-12 from a nationally representative sample of roughly 130 private and public schools in years 1994-95. Every pupil attending the sampled schools on the interview day is asked to complete a questionnaire (in-school survey) containing questions on respondents’ demographic and behavioral characteristics, education, family background and friendships. This sample contains information on roughly 90,000 students. A subset of adolescents selected from the rosters of the sampled schools, about 20,000 individuals, is then asked to complete a longer questionnaire containing more sensitive individual and household information (in-home survey and parental data).

For the purposes of our analysis, the most interesting aspect of the AddHealth data is the information on friendships. Indeed, the friendship information is based upon actual friend nominations. Pupils were asked to identify their best friends from a school roster (up to five males and five females). Friend nominations, however, are not always reciprocal. If \( i \) nominates \( j \) as a friend, we set \( g_{ij} = 1 \), which implies that \( i \) is influenced by \( j \) according to the best-reply function (5). In other words, \( i \) can be influenced by \( j \) even though \( j \) does not consider \( i \) as his/her best friend. For each school, we thus obtain all the networks of (best) friends. By matching the identification numbers of the friendship nominations to respondents’ identification numbers, one can obtain information on the characteristics of nominated friends.

The in-home questionnaire contains an extensive set of questions on juvenile delinquency, that are used to construct our dependent variable. Specifically, the AddHealth dataset contains information on 15 delinquency items. The survey asks students how often they participate in each of these activities during the past year. Each response is coded using an ordinal scale ranging from 0 (i.e. never participate) to 1 (i.e. participate 1 or 2 times), 2 (participate 3 or 4 times) up to 3 (i.e. participate 5 or more times). To derive quantitative information on crime activity using qualitative answers to a battery of related questions, we calculate an index of delinquency involvement for each respondent. The delinquency index ranges between 1.51 and 11.04, with mean equal to 2.35 and standard deviation equal to 1.09. Non-criminal individuals are defined as those who report

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10. The limit in the number of nominations is not binding (even by gender). Less than 1% of the students in our sample show a list of ten best friends.
11. Namely, painting graffiti or signs on someone else’s property or in a public place; deliberately damaging property that didn’t belong to you; lying to your parents or guardians about where you had been or whom you were with; taking something from a store without paying for it; getting into a serious physical fight; hurting someone badly enough to need bandages or care from a doctor or nurse; running away from home; driving a car without its owner’s permission; stealing something worth more than $50; going into a house or building to steal something; use or threaten to use a weapon to get something from someone; selling marijuana or other drugs; stealing something worth less than $50; taking part in a fight where a group of your friends was against another group; acting loud, rowdy, or unruly in a public place.
12. Respondents listened to pre-recorded questions through earphones and then entered their answers directly on laptop computers. This administration of the survey for sensitive topics minimizes the potential for interview and parental influence, while maintaining data security.
13. This is a standard factor analysis, where the factor loadings of the different variables are used to derive the total score.
never participating in any delinquent activity. This data allows us to get valid information on 6,993 (criminal and non-criminal) students distributed over 1,596 networks, with network size ranging between 2 and 1,050 individuals. This sample is used to investigate the decision to commit crime (see Section 5.4.1). The analysis of the key player policy in crime focuses on networks of criminals only. Because the strength of peer effects may vary with network size (see Calvó-Armengol et al., 2009), the large variation in network size forces us to exclude networks at the extremes of the network size distribution. Indeed, our theoretical model assumes homogenous peer effects in crime \( \phi \), and we thus need to estimate only one peer-effect parameter.\(^{15}\)

Our selected sample consists of 1,297 criminals distributed over 150 networks, with network size ranging between 4 and 77 individuals.\(^{16}\) The mean and standard deviation of network size are roughly 9 and 12 pupils. On average, delinquents declare having 1.33 delinquent friends with a standard deviation of 1.29.

Table A.1 in Appendix B provides a description of the control variables used in our study and Table A.2 collects the summary statistics distinguishing between criminals and non criminals.\(^{17}\) As expected, Table A.2 shows that delinquent students are less likely to be a female, religious, attached to the school and to come from less educated families than non-delinquent students. They are also more likely to reside in urban areas. Table A.2 also shows that the final sample we use does not lose representativeness.

5 Peer effects and network centrality

5.1 Econometric model

To determine the key player, first we need to estimate the endogenous peer effect parameter \( \phi \) in the best-reply function (5). Let \( \bar{r} \) be the total number of networks in the sample, \( n_r \) be the number of individuals in the \( r \)th network \( g_r \), and \( n = \sum_{r=1}^{\bar{r}} n_r \) be the total number of sample observations. Let \( x_{i,r} = (x_{i,r}^1, \cdots, x_{i,r}^{M})' \). The econometric model corresponding to the best-reply function (5) of agent \( i \) in network \( g_r \) can be written as

\[
y_{i,r} = \phi \sum_{j=1}^{n_r} g_{i,j,r} y_{j,r} + x_{i,r}' \beta_1 + \frac{1}{\bar{g}_{i,r}} \sum_{j=1}^{n_r} g_{i,j,r} x_{i,j,r}' \beta_2 + \eta_r + \epsilon_{i,r},
\]

where \( \bar{g}_{i,r} = \sum_{j=1}^{n_r} g_{i,j,r} \) is the total number of friends of individual \( i \) belonging to network \( r \) and \( \epsilon_{i,r} \)'s are i.i.d. innovations with zero mean and variance \( \sigma^2 \) for all \( i \) and \( r \). In matrix form, model (9) can be written as

\[
y = \phi G y + X \beta_1 + G^* X \beta_2 + \eta + \epsilon,
\]

For a sample with \( \bar{r} \) networks, stack up the data by defining \( y = (y_1', \cdots, y_{\bar{r}}')', X = (X_1', \cdots, X_{\bar{r}}')' \),

---

\(^{14}\)The large reduction in sample size with respect to the original AddHealth sample is mainly due to missing values in variables and to the network construction procedure. Indeed, roughly 20% of the students do not nominate any friends and another 20% cannot be correctly linked (for example because the identification code is missing or misreported).

\(^{15}\)From an empirical point of view, the estimation of heterogenous peer effects requires the exclusion of network fixed effects, which are an important aspect of our identification strategy, allowing us to control for unobserved factors.

\(^{16}\)Our results, however, do not depend crucially on these network size thresholds. They remain qualitatively unchanged when moving the network size window slightly.

\(^{17}\)Information at the school level, such as school quality and teacher/pupil ratio, is unnecessary given our fixed effects estimation strategy.
\[ \epsilon = (\epsilon'_1, \ldots, \epsilon'_r)', \quad G = \text{diag}\{G_r\}_{r=1}^r, \quad G^* = \text{diag}\{G^*_r\}_{r=1}^r, \quad L = \text{diag}\{l_n\}_{n=1}^N \quad \text{and} \quad \eta = (\eta_1, \ldots, \eta_r)', \]

where \( \text{diag}\{A_k\} \) is a “generalized” block diagonal matrix in which the diagonal blocks are \( m_k \times n_k \) matrices \( A_k \)’s. For the entire sample, the model is

\[ y = \phi G y + X \beta_1 + G^* X \beta_2 + L \eta + \epsilon. \quad (10) \]

In model (10), \( \phi \) represents the endogenous effect, where an agent’s choice/outcome may depend on those of his/her friends about the same activity; and \( \beta_2 \) represents the contextual effect, where an agent’s choice/outcome may depend on the exogenous characteristics of his/her friends. It is well known that endogenous and contextual effects cannot be separately identified in a linear-in-means model due to the reflection problem, first formulated by Manski (1993). We will discuss the identification of endogenous and contextual effects in the following subsection.

The vector of network fixed effects given by \( \eta \) captures the correlated effect where agents in the same network may behave similarly as they have similar unobserved individual characteristics or they face a similar (institutional) environment. The network fixed effect serves as a remedy for the selection bias that originates from the possible sorting of individuals with similar unobserved characteristics into a network. The underlying assumption is that such unobserved characteristics are common to the individuals within each network. This is extremely reasonable in our case study where the networks are extremely small (see Section 4). 18

From the best-reply function (5), the network fixed effect also captures the deterrence effect on crime (pf in the theoretical model). Indeed, because in our sample networks are within schools, the use of network fixed effects also accounts for differences in the strictness of anti-crime regulations across schools (e.g. differences in the expected punishment for a student who is caught possessing illegal drugs, stealing school property, verbally abusing a teacher). As a result, instead of directly estimating deterrence effects (i.e. including in the model specification observable measures of deterrence, such as local police expenditures or the arrest rate in the local area), we focus our attention on the estimation of peer effects in crime, accounting for network fixed effects. 19

In the econometric model, we allow network fixed effects \( \eta \) to depend on \( G, G^* \) and \( X \) by treating \( \eta \) as a vector of unknown parameters (as in a fixed effect panel data model). When the number of groups \( r \) is large, we may have the incidental parameter problem. To avoid the incidental parameter problem, we transform (10) using the deviation from group mean projector \( J = \text{diag}\{J_r\}_{r=1}^r \), where \( J_r = I_{n_r} - \frac{1}{n_r} l_n l_n' \). This transformation is analogous to the within transformation for the fixed effect panel data model. As \( JL = 0 \), the transformed model is

\[ J y = \phi J G y + J X \beta_1 + J G^* X \beta_2 + J \epsilon. \quad (11) \]

The proposed estimators and identification conditions are based on the transformed model (11).

18 In fact, the use of an over-identifying restrictions test (Lee, 2007b) supports the validity of this assumption (see section 5.3).

19 The identification of deterrence effects is a difficult empirical exercise because of the well-known potential simultaneity and reverse causality issues (Levitt, 1997).
5.2 Identification of the peer effects

In this subsection, we will first review the identification results when the endogenous effect takes the form of a local-average effect. Then, we will present new identification results when the endogenous effect takes the form of a local-aggregate effect.

5.2.1 The local-average endogenous effect

Bramoullé et al. (2009) and Lee et al. (2010) have considered the identification of the following network model

\[
y = \phi G^* y + X \beta_1 + G^* X \beta_2 + L \eta + \epsilon. \tag{12}
\]

In (12), the term \( G^* y \) represents the average effort level of an individual’s friends. Therefore, we refer to this specification as the local-average model.

To estimate the transformed local-average model

\[
J y = \phi J G^* y + J X \beta_1 + J G^* X \beta_2 + J \epsilon
\]

using linear IV estimators, the deterministic part of the right-hand-side (RHS) variables, \([E(J G^* y), J X, J G^* X]\), needs to have full column rank for large enough sample size. When \((I - \phi G^*)\) is nonsingular, from the reduced-form equation of the local-average model, we have

\[
E(J G^* y) = J G^* X \beta_1 + (J G^{*2} X + \phi J G^{*3} X + \cdots) (\phi \beta_1 + \beta_2) \tag{13}
\]

If \(\phi \beta_1 + \beta_2 = 0\), then \(E(J G^* y) = J G^* X \beta_1\). Thus, the model cannot be identified as \([E(J G^* y), J X, J G^* X]\) does not have full column rank. On the other hand, if \(\phi \beta_1 + \beta_2 \neq 0\), then \(J G^{*2} X, J G^{*3} X,\) etc. can be used as instruments for the endogenous effect variable \(J G^* y\). The term \(G^{*2} X\) represents the characteristics of “second-order” indirect friends. If individuals \(i, j\) are friends and \(j, k\) are friends, it does not necessarily imply that \(i, k\) are also friends. Thus, the intransitivity in social connections provides an exclusion restriction to identify endogenous and contextual effects. Based on this important observation, Bramoullé et al. (2009) have argued that the local-average model is identified if \(I, G^*, G^{*2}, G^{*3}\) are linearly independent.

5.2.2 The local-aggregate endogenous effect

In model (10), the term \(G y\) represents the aggregate effort level of an individual’s friends. Therefore, we refer to this specification as the local-aggregate model. When \((I - \phi G)\) is nonsingular, from the reduced-form equation of (10), we have

\[
E(J G y) = J(G X + \phi G^2 X + \cdots) \beta_1 + J(G G^* X + \phi G^2 G^* X + \cdots) \beta_2 + J(GL + \phi G^2 L + \cdots) \eta. \tag{14}
\]

So even if \(\beta_1 = \beta_2 = 0\), the deterministic part of the RHS variables in (11), \([E(J G y), J X, J G^* X]\), can still have full column rank as \(E(J G y) = J(GL + \phi G^2 L + \cdots) \eta\). According to Definition 1

\footnote{In a linear-in-means model, individuals are affected by all individuals belonging to their group and by nobody outside the group. Hence, simultaneity in behavior of individuals in the same group introduces a perfect collinearity between the endogenous effect and the contextual effect (i.e. the so-called reflection problem, Manski, 1993).}
(Section 3), the matrix $GL + \phi G^2 L + \cdots$ collects the Katz-Bonacich centrality for all individuals. The leading order term of the Katz-Bonacich centrality matrix is $GL = \text{diag}\{G_r l_{n_r}\}_{r=1}^R$, where $G_r l_{n_r}$ is a vector of row-sums of $G_r$. When considering social network interactions, $G_r l_{n_r}$ has a natural interpretation, with its $i$th element being the number of friends student $i$ nominates. Therefore, for the local-aggregate model, besides the characteristics of friends, the number of friends can be used as an additional instrument for the endogenous effect variable.

Let $Z = [G_l, X, G^* X]$. For identification of $(10)$ via $(11)$ through linear IV estimators, $E(JZ)$ needs to have full column rank for large enough sample size. The following proposition gives sufficient conditions for the rank condition. Henceforth, let $c$ (possibly with subscripts) denote a constant scalar that may take different values for different uses.

**Proposition 2** When $G_r$ has non-constant row sums for some network $r$, $E(JZ)$ has full column rank if: (i) $I_{n_r}, G_r, G^*_r, G, G_r^*$ are linearly independent and $\beta_1, \beta_2, \eta_r$ are not all zeros; or (ii) $G_r G^*_r = c_1 I_{n_r} + c_2 G_r + c_3 G^*_r$ and $\Lambda_1$ given by $(29)$ has full rank.

When $G_r$ has constant row sums such that $\bar{g}_{i,r} = \bar{g}_r$ for all $r$, $E(JZ)$ has full column rank if: (iii) $I, G, G^*, GG^*, G^2, GG^2$ are linearly independent and $\beta_1, \beta_2$ are not both zeros; or (iv) $I, G, G^*, GG^*, G^2$ are linearly independent, $GG^2 = c_1 I + c_2 G + c_3 G^* + c_4 GG^* + c_5 G^2$, and $\Lambda_2$ given by $(30)$ has full rank; or (v) $\bar{g}_r = \bar{g}$ for all $r$, $I, G^*, G^2, G^3$ are linearly independent, and $\phi_1 \bar{g} \beta_1 + \beta_2 \neq 0$.

The proof of Proposition 2 is given in Appendix C. From Proposition 2, we can see that, for a given network, sometimes identification of the local-aggregate model is easier to achieve than the local-average model. Figure 1 gives some examples where identification is possible for the local-aggregate model but fails for the local-average model. First, consider a dataset where each network is represented by graph (a) of Figure 1 (a star-shaped network). The corresponding adjacency matrix $G$ is a block-diagonal matrix with diagonal blocks $G_r$ representing graph (a). For the row-normalized adjacency matrix $G^*$, it is easy to see that $G^5 = G^*$. Therefore, it follows from Proposition 5 of Bramoullé et al. (2009) that the local-average model (12) is not identified. On the other hand, as $G_r$ corresponding to the graph (a) has non-constant row sums and $I_{n_r}, G_r, G^*_r, G, G_r^*$ are linearly independent, it follows from our Proposition 2(i) that the local-aggregate model can be identified for this network.

[Insert Figure 1 here]

Graphs (b) and (c) in Figure 1 provide other examples where the local-average model cannot be identified while the local-aggregate model can be. Consider a dataset that consists of two types of networks. The first $\bar{r}_1$ networks are represented by graph (b) of Figure 1 (a regular or circle network). The rest $\bar{r}_2$ networks are represented by graph (c) of Figure 1 (a bi-partite network). Suppose $\bar{r}_1 > 0$, $\bar{r}_2 > 0$ and $\bar{r}_1 + \bar{r}_2 = \bar{r}$. The corresponding adjacency matrix $G$ is a block-diagonal matrix with the first $\bar{r}_1$ diagonal blocks $G_{1r}$ representing graph (b) and the rest $\bar{r}_2$ diagonal blocks $G_{2r}$ representing graph (c). For the row-normalized adjacency matrix $G^*$, it is easy to see that $G^5 = G^*$. Therefore, it follows from Proposition 5 of Bramoullé et al. (2009) that the local-average model (12) is not
identified. On the other hand, as $G_1$ and $G_2$ have different row sums, $I, G, G', GG', G^2$ are linearly independent and $GG^2 = G$. Therefore, the local-aggregate model can be identified by our Proposition 2(iv).

5.3 Estimation methods and results

We estimate the local-aggregate network model (10) using the 2SLS and GMM estimators proposed in Liu and Lee (2010). As discussed above, for the local-aggregate model, besides the “conventional” instruments $G^2 X$ based on characteristics of friends’ friends (Bramoullé et al., 2009), the number of friends given by $GL$ can be used as additional instruments to improve estimation efficiency. The GMM estimator uses additional quadratic moment conditions and can be helpful when the conventional instruments are weak. However, as $GL$ has $\bar{r}$ columns, there would be a large number of instruments if the number of networks $\bar{r}$ is large. As a result, the 2SLS and GMM estimators with the instruments $GL$ may have the “many-instrument” bias if $\bar{r}$ is large relative to the sample size. Liu and Lee (2010) have suggested a bias-correction procedure based on the estimated leading-order “many-instrument” bias. The details of the 2SLS and GMM estimators considered in this empirical study are given in Appendix D.

The validity of our identification strategy and the moment conditions employed by the 2SLS and GMM estimators rests on the exogeneity of the adjacency matrix $G$. We test the exogeneity of $G$ using the over-identifying restrictions (OIR) test (Lee, 1992). If the OIR test cannot reject the null hypothesis that the moment conditions are correctly specified, then it provides evidence that $G$ is uncorrelated with the error term, when $X$, contextual effects and network fixed effects are controlled.

[Insert Table 1 here]

Table 1 collects the estimation results of the local-aggregate network model (10). The first stage partial F-statistics (see Stock et al., 2002 and Stock and Yogo, 2005) reveal that our instruments are quite informative. Hence, the 2SLS and GMM deliver similar results. The GMM estimators are only more precise in the estimation of $\phi$. The $p$-value of the OIR test is larger than conventional significance levels, which provides evidence on the exogeneity of network structure (conditional on $X$, $G'X$ and network fixed effects). All our estimates of $\phi$ are within the parameter space given by $\phi < 1/\mu_1(G)$. Such a condition is needed to guarantee the existence of the equilibrium in our model (equation (6) in Section 3). According to the bias-corrected many-IV GMM estimator, in a group of two friends, a standard deviation increase in the level of delinquent activity of the friend translates into a roughly 5 percent increase of a standard deviation in the individual level of activity. If we consider an average group of 4 best friends (linked to each other in a network), a standard deviation increase in the level of delinquent activity of each of the peers translates into a roughly 17 percent increase of a standard deviation in the individual level of activity. This is a non-negligible effect, especially given our long list of controls.
5.4 Robustness of the estimation results

We would like to propose different robustness checks for the estimation of \( \phi \) in the local-aggregate network model (10).

5.4.1 Endogenous participation in criminal activities

First, we introduce the endogenous participation in criminal activities into the model (10). We consider a type-II Tobit model. We specify the participation equation as

\[
y_{i\tilde{n}}^* = X_{1\tilde{n}} \gamma + \epsilon_{1\tilde{n}},
\]

where \( \tilde{n} \) is the total number of individuals in the population, \( y_{i\tilde{n}}^* = (y_{i1}^*, \ldots, y_{i\tilde{n}}^*)' \), \( X_{1\tilde{n}} = (x_{11}, \ldots, x_{\tilde{n}1})' \), and \( \epsilon_{1\tilde{n}} = (\epsilon_{11}, \ldots, \epsilon_{n1})' \). Agent \( i \) will become a criminal if and only if \( y_{i1}^* > 0 \). For the individuals who decide to be criminals, the outcome equation given by (10) determines the crime effort levels.

Without loss of generality, we assume the first \( n \) (of the \( \tilde{n} \)) individuals will choose to become criminals. By assuming joint normality of a criminal’s error terms across the participation and outcome equations, the selection-bias-corrected outcome equation is given by

\[
y = \phi G y + X \beta_1 + G' X \beta_2 + L \eta + \sigma_{12} \lambda + \epsilon^*,
\]

where \( \lambda = \left[ \lambda(x_{11}^\gamma), \ldots, \lambda(x_{1n}^\gamma) \right]' \) and \( \lambda(x_{1i}^\gamma) \) is the inverse Mills ratio (IMR) for criminal \( i \). Equation (16) can be estimated following Heckman’s two-step approach, which is detailed in Appendix E.1.

Observe that, if \( X_{1\tilde{n}} \) in (15) contains the same set of exogenous variables as \( X \) in (16), then the identification of the IMR term in (16) solely relies on the nonlinear functional form of \( \lambda(\cdot) \). As \( \lambda(\cdot) \) is approximately linear in a wide range of its domain, this identification can be weak. Hence, we need to find variables in \( X_{1\tilde{n}} \) that are excluded from \( X \). Our exclusion restrictions are inspired by the entry model of Ballester et al. (2010) according to which there is a cost that individuals have to pay when entering criminal activity (sunk cost) and individual characteristics are the key determinants of the crime participation. The cost can also be interpreted as the outside option of non-criminals. We then use two types of exclusion restrictions.

The first instrument captures the idea that there is a moral cost of committing crime. Children coming from families with stronger moral and family values may pay an higher “entry cost”. However, once a crime is committed for the first time (hence parents and relatives are already disappointed), there is no additional cost of this sort when committing more crimes. To measure this moral cost, we use the information on religion practice, which is the answer to the following question: “In the past 12 months, how often did you attend religious services”, coded as 1= never, 2= less than once a month, 3= once a month or more, but less than once a week, 4= once a week or more, coded as 5 if the previous is skipped because of response “none” to the question: “What is your religion?” (see

\footnote{Another interpretation is that kids from families with strong moral values can have a higher cost of anticipating being found out. In that case, only kids with low “disappointing their parents” price will become criminals. Then, once a kid has decided to become a criminal, this anticipation cost becomes insignificant.}
Appendix B). Table 2 (upper panel, column IV1: moral cost) reports the first stage of the Heckman selection model when we use this instrument (Religion Practice). One can see that it is a strong predictor of criminal activity (with an expected negative association).

The second instrument aims to capture the idea that there are outside options for crime in terms of activities and money. A student receiving a generous weekly allowance from his/her parents and/or having money from other jobs and/or being busy in other activities is less likely, in the first place, to consider crime activity as an appealing option. We have thus constructed an indicator capturing the relevance of the outside options for each student. We use a similar factor analysis that we employed when constructing an index of criminal activity to derive a composite score using the answers to the following questions: (i) During the past week, how many times did you do work around the house, such as cleaning, cooking, laundry, yardwork, or caring for a pet? (ii) During the past week, how many times did you go rollerblading, roller-skating, skate-boarding, or bicycling? (iv) How much money do you earn in a typical non-summer week from all your jobs combined? (v) How much is your allowance each week? If you don’t receive your allowance weekly, how much would it be each week? (see Appendix B). Table 2 (upper panel, column IV2: moral cost & outside options) reports the first stage of the Heckman selection model when we add this instrument (Outside Options). It appears that this outside option indicator seems to be a strong predictor of criminal activity and the relationship is of the predicted (negative) sign.

[Insert Table 2 here]

In Table 2, we also report the estimation results of the selection-bias-corrected outcome equation (16) without exclusion restrictions (column 1), with the moral cost exclusion restriction (column 2), and with both the moral cost and outside option exclusion restrictions (column 3). We find that the results are qualitatively the same as the results reported in Table 1, which provides evidence that the estimation results are robust to endogenous crime participation.22,23

5.4.2 Sampling on criminals

Second, we take into account a possible sampling issue because questions on delinquency activities are only asked to the students in the in-home sample.24 Thus, if a criminal has a friend who is not in the in-home sample, we do not know if this friend is a criminal or not. As a result, when constructing criminal networks this node is excluded from the network and we face a possible misspecification of

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22 The significant estimate of $\sigma_{12}$ suggests that the IMR term is an omitted variable in the error term of the outcome equation without selection-bias correction. The OIR test for the finite-IV 2SLS estimator of the outcome equation without selection-bias correction suggests that the instruments are uncorrelated with the error term (including the omitted IMR). This evidence is consistent with the robustness of estimation results with respect to endogenous crime participation.

23 The inclusion of “religion practice” in the outcome equation returns an insignificant estimated coefficient. The estimation results which are obtained using only the outside option indicator as exclusion restriction remain roughly unchanged.

24 This is a different sampling issue from the one studied by Chandrasekhar and Lewis (2012) and Liu (2013) where only a subsample of the population is surveyed to nominate their friends. For the AddHealth data, all the students in a school are surveyed to nominate their friends but a student’s crime effort cannot be observed if he/she is not in the in-home subsample.
the network topology (if this friend is criminal).

As a robustness check, we estimate our model using the subsample of students whose nominated friends are all in the in-home sample. For those individuals the information on the network connection is complete. The estimates are reported in column (1) of Table 3 and remain largely unchanged with respect to those reported in the first column of Table 1.\(^{25}\)

[Insert Table 3 here]

### 5.4.3 The role of non-criminal friends

Finally, we consider the role of non-criminal friends. In our theoretical model, a criminal’s effort level depends on the aggregate effort level of his/her friends. As the crime effort level of a non-criminal friend is zero, a non-criminal friend has no direct influence on a criminal’s effort level. However, non-criminal friends may affect the crime effort decision through the following two channels: (i) a non-criminal friend may bridge two criminals and pass on the endogenous peer effect; (ii) a non-criminal friend’s characteristics may affect a criminal’s crime effort decision through the contextual effect.

Regarding (i), we estimate our model using a subsample of criminals whose friends are all criminals. For these criminals (who only nominate criminal friends), there is clearly no uncaptured effect of non-criminal friends. The results of this robustness check are contained in column (2) of Table 3. Our estimate of peer effects is roughly unchanged with respect to those reported in the first column of Table 1, which suggests that the “bridge” effect of non-criminal friends is negligible.\(^{26}\)

Regarding (ii), we repeat our regression analysis using the entire network of social contacts, i.e. both criminals and non-criminals, thus considering the average characteristics of non-criminal friends as additional regressors in model (10). Observe that, in this exercise, because we also consider non-criminal friends in the network, our IVs (which are based on the characteristics of indirect friends) might change (because the indirect friends might be different). The estimation results are contained in the last column of Table 3 and are, again, very similar. Our robustness checks thus show that the influence of non-criminal friends does not seem to matter much in the estimation of peer effects.

### 6 Who is the key player?

Let us now calculate empirically who is the key player in each of our real-world networks. For this part, we will use both the static model of Section 3 but also, as a robustness check, the dynamic network formation model developed in Appendix A.2. We will structurally simulate these two...
models. For the dynamic model, to study the convergence of the dynamic network formation model after the removal of the key player, we assume that the criminal networks observed in the AddHealth data in 1994/1995 are equilibrium networks and thus, to guarantee that this is true, we need to set the cost of forming links high enough so that no one in the observed network has incentive to form new links. In Appendix A.2, we explain in detail how we do this.

6.1 Simulation results

As described in Section 4, we have 1,297 criminals distributed over 150 networks. For the dynamic model, we only retain networks that satisfy the eigenvalue condition \( \phi \eta_1(G_t) < 1 \), as \( G_t \) evolves.27 Fortunately, only 5 networks fail to satisfy this condition and thus we end up with 1,038 criminals distributed over 145 networks. Figure 2 displays the distribution of these 145 networks by their size. The distribution is clearly very skewed to the left as we focus on small networks. The average network is size 7. The networks contain a minimum of 4 and a maximum of 64 delinquents.

[Insert Figure 2 here]

In Figure 3, we investigate the three following questions concerning the key player: Is he/she the most active delinquent in the network (left panel)? Does he/she have the highest betweenness centrality (middle panel)? Is the key player in the static network model the same as in the dynamic model (right panel)?

Figure 3 indicates that it is not straightforward to determine which delinquent should be removed from a network by only observing his or her criminal activities or position in the network.29 Indeed, Figure 3, left panel, shows that, in many cases, the key player is not the most active delinquent (i.e. the delinquent with the highest Katz-Bonacich centrality) in the network. For example, for networks of size 4, 66 percent have key players who are not the most active delinquents while, for networks with six delinquents, this number is 76%. If we now consider Figure 3, middle panel, we find that an even higher number of key players do not have the highest betweenness centrality in the network. Indeed, for networks of size 4, 55 percent of key players do not have the highest betweenness centrality in the network while, for networks of a bigger size, this number can be over 80 percent (for networks of size 9 and 10, this number is 100 percent). As a result, if a planner does not use a key-player policy but his/her intuition or “a rule of thumb” like targeting the most active criminal or the one who bridges different clusters in a network (i.e. highest betweenness centrality), then he/she will, in many cases, target the “wrong” person, i.e. not the delinquent who will reduce total crime in the network the most.

27 In fact, this condition needs to be satisfied for all networks during the dynamic link-formation process. Since the eigenvalue of a network (and thus the largest eigenvalue condition) changes over time, we use a sufficient condition: \( \phi \sqrt{\sum_{i,j} g_{ij} + n - 1} < 1 \), which uses an upper bound on the largest eigenvalue (see Corollary 1 page 1409 in Ballester et al., 2006). The main advantage of this new condition is that one does not need to calculate the largest eigenvalue of the network at each period in time.

28 The betweenness centrality is another centrality measure that counts the number of shortest paths that goes through an agent (see Wasserman and Faust, 1994).

29 In Figure 3, we consider only networks of size between 4 and 10; there are 130 networks of this size. We only consider networks of size between 4 and 10 to save space and because, for networks larger than 10, there are, usually, only one or two networks for each network size. For example, there is only one network with 12 individuals, one with 13 individuals and one with 15 individuals.
Finally, if we look at the right hand panel of Figure 3, we see that in most cases (90 percent for networks of size 4 and 100 percent for networks of sizes 8 and 10), the key players are the same in the static and the dynamic models, meaning that the invariant assumption is relatively good in our context. This is because our networks are relatively small and we set the link-formation cost relatively high to ensure that the observed networks in the data are in equilibrium. As a result, the convergence to the new equilibrium network is very fast in the simulation exercises with an average of 0.45 days and a maximum of 5 days and the equilibrium networks in the dynamic model are usually quite similar to the initial networks right after a delinquent is removed.

[Insert Figure 3 here]

Figure 4a shows how much change in the network density occurs after the removal of the key player where, on the left panel, we consider the static (or invariant) network case while, on the right panel, the dynamic network-formation model is displayed. We see that there is no clear pattern. The density could either increase or decrease after the removal of the key player. We also see that there is little difference between the static and the dynamic model for the same reasons given above. In Figure 4b, we examine the density change from the static network to the dynamic network (after the removal of the key player). In that case, the network density increases in the dynamic network formation process as compared to the static model.

[Insert Figures 4a and 4b here]

6.2 Characteristics of the key player

Once we have identified the key player for each network, we can draw his or her “profile” by comparing the characteristics of these key players with those of the other criminals in the network. Table 4 displays the results only for the variables where the difference in means between these two samples is statistically significant.

Compared to other criminals, key players are less likely to be a female, are less religious, belong to families whose parents are less educated and have the perception of being socially more excluded. They also feel that their parents care less about them, are less likely to come from families where both parents are married and have more trouble getting along with teachers. An interesting feature is that key players are more intelligent (i.e. higher mathematics scores) than the average criminal and are more likely to have friends who are older (i.e. in higher grades), more religious, more intelligent and whose parents are more educated. Also, even though key players themselves do not have better self-esteem, are not more physically developed nor are they more likely to be urbanites than other criminals.31,32

30 Network density is simply the fraction of links present in a network over all possible ones. It ranges from 0 to 1 as networks get denser.
31 Summary statistics of the other characteristics of the key players, as well as that of their friends are not reported for brevity. They remain available upon request.
32 Our analysis of the key player has also been performed for petty crimes and more serious crimes separately. The results are available upon request.
7 Policy implications

Let us address the fundamental policy issues of the key player. First, we further develop the qualitative approach (simulations) of Section 6 to evaluate the benefits versus costs of a key-player policy. Second, we provide evidence that there exist data on criminal networks and discuss the extent to which our analysis can be used in practice to address general policies against crime. Finally, we show that the methodology developed in this paper can be used to address policies in other activities such as financial networks, R&D networks, social networks in developing economies, political networks and tax-evasion networks.

7.1 Qualitative approach of the key-player policy using the AddHealth data

The first key issue is when a key-player policy should be implemented and when it should not. We perform a simulation exercise comparing the key player policy with another “potential” public policy from which relevant lessons could be drawn.

For each of the 145 networks, we calculate the reduction in total crime following the removal of the key player. We report, in Figure 5, the relationship between crime reduction and network size where, in the left panel, we consider the static (or invariant) network case while, in the right panel, the dynamic network-formation model is displayed. First, not surprisingly, there are nearly no differences between the static and the dynamic model. Second, one can see that there are very large variations in crime reduction between different networks. Indeed, for some networks, total crime is reduced by less than 5 percent while, for other networks, the reduction in crime can be as high as 35 percent. Moreover, the crime reduction is much more important in small networks than in large networks. This is because we remove only one key player, and in large networks the effect is clearly lower than in small networks.

Figure 6 plots the average crime reduction for all the 145 networks when a key-player policy (solid curve with circles), a random-target policy (solid curve with arrows) and a policy that removes the most active criminal (dash curve) is implemented. We believe that it is especially important to assess the potential benefit of a key player policy to a policy where the individuals who are identified as “high risk” for delinquency are targeted. It is clearly difficult to justify profiling since characteristics such as race and gender are correlated with the key player (see Section 6.2), and targeting them rather than the most active (i.e. those who are participating in the most criminal activity) players may be controversial ex post. This is why we want to evaluate the efficiency of the key-player policy with respect to a policy that targets the most active criminals in a network.

To plot Figure 6, we have put together networks of the same size and calculated the average

\[
\text{This reduction is calculated as: } \frac{[\text{Expected total crime of the converged network (before the removal of the key player)} - \text{Expected total crime of the converged network (after the removal of the key player)}]}{\text{Expected total crime of the converged network (before the removal of the key player)}}.
\]
crime reduction for this network size under the three policies. For example, for all networks of size 4 (horizontal axis), the average crime reduction is 29.94 percent on average when the key-player policy is implemented, it is 23.86 percent for the random-target policy and around 25 percent when the most-active criminal policy is implemented. The results displayed in Figure 6 confirms the fact that a key-player policy is important since the difference in crime reduction between these three policies can be extremely large, especially for big networks.\textsuperscript{34} We believe that we obtain these results because targeting key players generate large \textit{multiplier and amplifying effects} as opposed to the two other policies. Indeed, targeting the key player, not only affects his/her criminal activities, but also the criminal activities of his/her direct friends, which, in turn, affects that of their direct friends, etc. In a random-target or most-active criminal policy, these chain effects are similar but the target is on the “wrong” person. Our simulations show that a key-player policy should be implemented when the crime reduction difference between a key-player and the other policies is relatively high. In the real-world, there are some administrative costs of collecting detailed data on the social networks linking individuals and on their criminal activity. However, in Section 7.2.1, we provide a list of data on criminal networks suggesting that the administrative costs of gathering information on network data are not that high.

\[\text{Insert Figure 6 here}\]

7.2 How the key-player policy can be useful in fighting crime

7.2.1 Data about criminal networks

In order to apply the key-player policy one needs to collect detailed data on the social networks linking individuals and on their criminal activity. Despite the importance of the key-player problem for law enforcement agencies, to the best of our knowledge, there is no widespread research on centrality analysis in large scale criminal networks to show if and how this kind of analysis can help in crime reduction and prevention or other efforts aiming at destabilizing the criminal network structure. The lack of research in this field can be explained with the perception that the sensitivity of crime data does not permit the release of public real-world crime data sets. In the real-world, there is a lot of information and data about criminal networks that could easily be used to implement our key-player policy. Observe, however, that one cannot just blindly apply our methodology. It clearly depends on the type of data one has. For example, if one has data on a network over time, as for example with the police data described in (ii) below, then one could check how well our model performs by comparing its prediction in terms of crime reduction after the removal of the key player with what happens in the real-world data. Let us now give a (selective) list of available network data:\textsuperscript{35}

\textsuperscript{34} For some networks, the key-player and the most-active criminal policy lead to nearly the same average crime reduction because key-players are also the most active criminals.

\textsuperscript{35} There is a recent literature which explores theoretical and empirical methods of inferring networks from node attributes and from functions of these attributes that are computed for connected nodes. In particular, Polanski and McVicar (2012) discuss the conditions, under which an underlying connection structure can be (probabilistically) recovered, and propose a Bayesian recovery algorithm. See also Costebander and Valente (2003) who show that centrality measures based on connectivity (rather than betweenness) are robust to mis-specifications in sociometric data, and thus open the door to estimations of centrality measures with incomplete samples of network data.
(i) Juvenile delinquency in schools (survey data): There are data similar to the AddHealth data for students in schools. For example, Weerman (2011) uses data from the Netherlands Institute for the Study of Crime and Law Enforcement (NSCR) “School Study”, a study that focused on social networks and the role of peers in delinquency with two waves, conducted in the spring of 2002 and 2003. Students were provided with a numbered list of all students in the same grade in their school and were asked to fill in the numbers of those fellow students they spend time with at school (“with which of these students do you associate regularly?”), with a maximum of ten possible nominations. Students’ delinquent behavior was measured using self-reports on a variety of offenses. The final sample consisted of 1,156 students in ten schools that participated in both waves.

(ii) Adult crime (police data): the police has in fact quite a lot of information on criminal networks. For example, in his book, Sarnecki (2001) was able to construct the network of all criminals in Sweden for several years. The way a link is defined is as follows. Each time two (or more) persons are suspected of a crime (co-offenders), the police in Sweden register this information. A link in a network is then created between individuals $i$ and $j$, i.e. $g_{ij} = g_{ji} = 1$, whenever individuals $i$ and $j$ are suspected of a crime together. Once we have this information, we can match each individual’s social security number with his/her characteristics (education, age, ethnicity, gender, etc.). In that case, we can literally apply all the tools developed in this paper and identify the key players in criminal networks.36

This type of information can be obtained from the police in many countries. Indeed, it is important to identify criminal networks in data resources readily available to investigators, such as police arrest data and court data. For example, Tayebi et al. (2011) use a data set made available by the “E” Division of the Royal Canadian Mounted Police (RCMP), as a result of a research memorandum of understanding between ICURS37, the RCMP and the Ministry of Public Safety and the Solicitor General. The data contain five years (2001-2006) of real-world crime data (arrest-data) and was made available for research purposes. These data were retrieved from the RCMP’s Police Information Retrieval System (PIRS), a large database system keeping information for the regions of the Province of British Columbia, which are policed by the RCMP. PIRS contains information about all reported crime events (4.4 million) and all persons associated with a crime (9 million), from complainant to charged.38 As for the Swedish data described above, Tayebi et al. (2011) defines a co-offending network, that is a network of offenders who have committed crimes together.

In the United States, there are also similar data. For example, Coplink (Hauck et al., 2002) was one of the first large scale research projects in crime data mining, and an excellent work in criminal network analysis. It is remarkable in its practicality, being integrated with and used in the workflow of the Tucson Police Department. Colink has information about the perpetrators’ habits and close associations in crime to capture the connections between people, places, events, and vehicles, based on past crimes. Xu and Chen (2005) built on this when they created CrimeNet Explorer, a frame-

36If a link is created, one can also check what the probability that these two persons are condemned is and also that this link re-appears over time (i.e. the two individuals are also suspected of another crime later on in their life).
37The Institute for Canadian Urban Research Studies (ICURS) is a university research centre at Simon Fraser University.
38In addition, PIRS also contains information about vehicles used in crimes (1.4 million), and businesses which were involved in crimes (1.1 million).
work for criminal network knowledge discovery incorporating hierarchical clustering, Social Network Analysis (SNA) methods, and multidimensional scaling.\textsuperscript{39}

(iii) Gang networks: McGloin (2004, 2005) use data from the Newark portion of the North Jersey Gang Task Force, a regional problem analysis project that sought to define the local gang landscape in Northern New Jersey. These data came from the experiential knowledge of representatives of various criminal justice agencies, including the Newark Police Department, Essex County Sheriff’s Office, Essex County Department of Parole, and Juvenile Justice Commission of New Jersey. In particular, groups of law enforcement officials from this variety of criminal justice agencies engaged in collective semi-structured interviews — 32 over the course of one year — that solicited information on the gang landscape. In particular, they provided information on known gang members, as well as the quantity and type of their respective associates. The classification of the profession of gang members in the questionnaire relied on New Jersey code, which defines a gang as three or more people who are, in fact, associated, that is people who have a common group name; identifying sign, tattoos, or other indices of association; and who have committed criminal offenses while engaged in gang-related activity.

Another example of available gang network data is the recent paper by Mastrobuoni and Patacchini (2012). They use a data set provided by the Federal Bureau of Narcotics on criminal profiles of 800 US Mafia members active in the 1950s and 1960s and on their connections within the Cosa Nostra network.\textsuperscript{40} Patacchini and Mastrobuoni shed light on the extent to which family relationships, community roots and ties, legal and illegal activities predict the criminal ranking of the “men of honor,” suggesting the main characteristics that can be used to detect criminal leaders.

7.2.2 How to implement a key-player policy

Once we have criminal network data, there are different ways of implementing a key-player policy. Indeed, once we have identified a key player in a network, one cannot put him/her in prison if he/she hasn’t committed any crime. However, different policies can be implemented to reduce crime using a key-player approach.

(i) First, the police can offer to the key player(s) incentives to leave the gang or the criminal network. For example, the police can offer them a job or a conditional transfer (by asking them to move to another city) or monitor them more. These types of policies have been implemented in the US. For example, in Canada, some gang members of criminal networks were persuaded to abandon gang life in return for needed employment training, educational training, and skills training (Tremblay et al., 1996).

(ii) Second, the police can target key players in a meaningful way. A very similar type of policy has actually been implemented in the US. Indeed, a recent innovation in policing that capitalizes on the growing evidence of the effectiveness of police deterrence strategies in the “focused deterrence” framework, which is often referred to as “pulling-levers policing” (Kennedy, 1998, 2008). This strategy was pioneered in Boston (Boston Gun Project) with the intent of understanding the purported

\textsuperscript{39}Xu and Chen (2005) expand the research in Xu and Chen (2003) and design a fully fledged system capable of incorporating outside data, such as phone records and report narratives, in order to establish stronger ties between individual offenders.

\textsuperscript{40}The information is also contained in a book by the United States Treasury Department (2007).
nexus of rising youth violence and use of firearms. As part of its problem analysis, representatives of various criminal justice agencies defined and characterized problematic local gangs (Braga et al., 2001; Kennedy et al., 1996, 1997, 2001). This process included elaborating on the relationships among the street gangs, which Kennedy et al. (1996, 1997, 2001) translated into sociograms illustrating connections within the gang landscape. This seemingly simple information was invaluable for the problem analysis and construction of Operation Ceasefire. This latter policy combines a strong law enforcement response with a “pulling levers” deterrence effort aimed at chronic gang offenders. The key to the success is to use a “lever pulling” approach, which is a crime deterrence strategy that attempts to prevent violent behavior by using a targeted individual or group’s vulnerability to law enforcement as a means of gaining their compliance. Operation Ceasefire was first launched in Boston and youth homicide fell by two-thirds after the Ceasefire strategy was put in place in 1996 (Kennedy, 1998). It was then implemented in Los Angeles in 2000: police beefed up patrols in the area, attempting to locate gang members who had outstanding arrest warrants or had violated probation or parole regulations. Gang members who had violated public housing rules, failed to pay child support, or were similarly vulnerable were also subjected to stringent enforcement (Tita et al., 2003). The strategy and tactics resulted from months of meticulous planning and coordination by 19 public and private agencies throughout the city and county of Los Angeles, all of whom came together to work with researchers in defining the problem and designing a response. The results from the law enforcement components were surprisingly good. In the area of Hollenbeck where gang activities were most active and enforcement was most intensive, both gang crime and violent crime fell. Operation Ceasefire in Los Angeles demonstrated the potential for using data-driven research to identify problems and design interventions, obtain the commitment of disparate criminal justice agencies to work together on a discrete problem, and secure the support of an array of partners in the community.

In early 2004, High Point Police Department (HPPD) officials in North Carolina decided to implement a policy similar to Operation Ceasefire. The logic model of the High Point intervention (High Point, NC) centered on three specific phases: the identification phase, the notification phase, and resource delivery. Following recommendations outlined by Eck et al. (2005), researchers identified the high-density violent crime areas that were influenced by coterminous drug markets (identification phase). Within each targeted area, narcotics investigators collaborated with probation and parole officers, reviewed prior drug incident reports, and conducted detailed surveillance, including the use of video-recorded purchases, for at least 1 month (and sometimes up to 3 months) where they identified key offenders within each site. The project team also worked to construct resolute cases to have the capacity to prosecute established and chronic drug dealers. The notification phase centered on the “call-in” sessions. The High Point team focused its intensive efforts in unique geographic contexts at distinct points in time, which included a call-in session in the West End Neighborhood in May 2004, in the Daniel Brooks Neighborhood in April 2005, in the Southside Neighborhood in June 2006, and in the East Central area in August 2007. Thus, identified offenders are either arrested based on their violent criminal histories (felony convictions) or called-in to notification sessions (nonviolent, nonfelony convictions). Regarding resource delivery, notified offenders completed a “needs assessment” the night of the call-in session, and they were subsequently assigned...
to local social service providers and community outreach officials for extensive follow-up. With this data, we believe that using the key-player methodology developed in this paper could lead to a more effective policy and a larger reduction in crime.

(iii) Finally, a key-player policy can also help for related issues. For example, there is a lot of debate in the US on how to allocate under-age adolescents who have committed an offence into juvenile facilities (detention centers). We know that there is a lot of learning in crime in prisons (Bayer et al., 2009). If we can rank these adolescents by their key-player centralities, then our model predict that we should put together the delinquents with high key-player centralities while grouping together young delinquents with low key-player centralities.

7.3 Using our methodology to find key players for other types of networks and activities

Our paper can also be seen as a methodological one. Our methodology can be applied to other contexts where network data are much easier to obtain. Let us provide some examples.

Financial networks

There is an abundance of information available on financial networks where links are usually bank loans. For example, Cohen-Cole et al. (2011) use transaction level data on interbank lending from an electronic interbank market, the e-MID SPA (or e-MID), which was the reference marketplace for liquidity trading in the Euro area from January 2002 to December 2009. Boss et al., 2004 analyze the network of Austrian banks in the year 2008 where links in the network represent exposures between Austrian-domiciled banks on a non-consolidated basis (i.e. no exposures to foreign subsidiaries are included). They have 770 banks with 2,454 links between them and an average 20.54 links. Basically, any central bank could provide this type of information. Using this type of data and the methodology developed in this paper, we could study the key player policy by reinterpreting the model where efforts would be the amount of loans between banks (Cohen-Cole et al. 2011). In that case, the key player policy would be: Which bank should we bail out in order to reduce systemic risk or maximize total activity? This is an extremely important issue because the recent financial crisis has shown that the problem is not necessary “too big to fail” but “too interconnected to fail”. Moreover, on a daily basis, central banks do monitor “risky” banks to prevent them from taking too many risks that could be harmful to the system. The problem is to define which banks are too risky. We believe that our framework, adapted to the financial networks, could help in designing effective key-player policies in the financial markets.

R&D networks

There is also a lot of information on R&D networks. For example, García-Canal et al. (2008) use alliance data stemming from the Thomson SDC Platinum data base. Three types of alliances are reported in the SDC database: (1) alliances that imply the transmission of an existing technology from one partner to another or to the alliance; (2) alliances that imply the cross-transfer of existing technologies between two or more partners or between these and the alliance, and (3) alliances that include the undertaking of R&D activities.

Another dataset that has been used is the one on interfirm collaborations from the NBER Patent Data File (Hall et al., 2001). These data provide information about all researchers who were involved
in creating the innovation along with information on the patenting company, its geographic location, and the types of technology involved. The names of the inventors are recorded along with the name of the corporate assignee claiming each patent. Hanaki et al. (2010) match the lists of inventors’ names across different assignee companies to see if they are connected via common inventors. If the same inventors work on a particular research project across two innovating companies, they ascribe the project to an R&D partnership and identify those companies as collaborators through the inventors. Longitudinal data on an evolving R&D network are then created by collecting annual snapshots of instantaneous networks.

Our model is easily adapted to R&D networks where efforts correspond to quantity produced and a link (i.e. an alliance) decreases the cost of producing goods. We can easily adapt our methodology to study the key-player policy by identifying the key firms that are the most critical for industry productivity. We can also answer the question: Which firm should we subsidize in order to generate maximum total activity?

**Networks in developing economies**

There are many network data for developing countries (see e.g. Fafchamps and Lund, 2003, who conducted a survey in four villages in the Cordillera mountains of northern Philippines between July 1994 and March 1995; Krishnan and Scibubba, 2009, who use the second round of the Ethiopian Rural Household Survey, conducted in 1994). There is also a recent paper by Banerjee et al. (2013) which study a problem related to the key-player issue. Their data come from a survey on 75 rural villages in Karnataka, India, that the authors conducted to obtain information on network structure and various demographics. The data are available online. They look at the diffusion of a microfinance program in these villages and show that, if the bank in charge of this program had targeted individuals in the village with the highest eigenvector centrality (a measure related to the Katz-Bonacich centrality), the diffusion of the microfinance program (i.e. take-up rates) would have been much higher. More generally, in developing countries, one could apply the key player policy to the issue of adoption of a new technology since there is strong evidence of social learning (Conley and Udry, 2010) and take-up rates in microfinance programs.

**Political networks**

Another application of a key player policy could be the political world. There is evidence that personal connections amongst politicians have a significant impact on the voting behavior of U.S. politicians (Cohen and Malloy, 2010). There is also evidence on lobbying to persuade public opinion when members of the public influence each other’s opinion (Lever, 2010). When people are deciding how to vote or which product to buy, they discuss their decision with people in their social environment. Competitions to persuade public opinion are the essence of political campaigns, but also occur in marketing between rival firms or in lobbying by interests groups on opposite sides of a legislation. Matching data on campaign contributions by lobby groups with data on co-sponsorship networks in the US House of Representatives, Lever (2010) finds that changes in both network in influence and pivot probabilities are significant predictors of changes in campaign contributions. Our key-player policy suggests that resources should be spent on key voters who have an influential position in the social network.
Tax evasion
There is strong evidence that there are strong social interaction effects in tax evasion (Fortin et al., 2007). Galbiati and Zanella (2012) estimate social externalities of tax evasion in a model where congestion of the auditing resources of local tax authorities generates a social multiplier. Identification is based on a contrast of the variance of tax evasion at different levels of aggregation. They use a unique data set that contains audits of about 80,000 small businesses and professionals in Italy and also provide an exact measure of reference groups that easily allows us to apply our model. They find a social multiplier of about 3, which means that the equilibrium response to a shock that induces an exogenous variation in mean concealed income is about 3 times the initial average response. This is a short-run effect that persists to the extent that auditing resources are not adjusted to internalize the congestion externality. In this context, a relevant question would be: Which person(s) should we target to reduce total tax evasion in a country?

8 Concluding remarks
This paper presents a methodology for determining the key player whose exclusion from his/her network would result in the greatest impact on the outcome of interest (adolescent crime rates in the case of our AddHealth data). We provide a structural estimation of the model, and a simulation describing how such a key player is identified, and furthermore, that this “greatest impact” key player cannot be accurately identified by the other measures prominent in the literature. This methodology provides a cost effective instrument for a wide variety of policy interventions. Implementation of a key-player based policy intervention in networks would result in drastic cost reductions by taking advantage of multiplier effects.

The key-player methodology has great scope for practical implementation, since it takes advantage of multiplier effects in naturally occurring networks. Given the right data (which in several instances already exist) it can be implemented in any context. Consider the recent Obama-Romney US presidential election, which recorded the most extensive campaign spending in US history. Implementation of our key-player methodology would shift attention away from “swing states” and rather target “swing voters”, who would have the greatest possible impact on voter decision within their social networks. Such an approach could easily have tempered the USD 2.3 billion total campaign cost. The cost of gathering the necessary data could not be expected to be more than a fraction of this. Alternatively consider vaccination in developing countries, targeting individuals who would reduce the spread of infectious diseases the most would be highly cost effective, freeing up resources to make more vaccination projects viable, and reducing the overall infection rate. Even where data is not yet freely available, implementing the key-player policy could be cost-effective overall, if the cost of data gathering is recouped by the cost saving in the actual policy intervention that stems from targeting key-players rather than all individuals.

References


A Finding the key player

A.1 Intercentrality measure in the invariant case

Let $M(g, \phi) = (I - \phi G)^{-1}$. Its entries $m_{ij}(g, \phi)$ count the number of walks in $g$ starting from $i$ and ending at $j$, where walks of length $k$ are weighted by $\phi^k$. The Katz-Bonacich centrality of node $i$ is $b_i(g, \phi) = \sum_{j=1}^{n} \alpha_j m_{ij}(g, \phi)$, and counts the total number of paths in $g$ starting from $i$ weighted by the $\alpha_j$ of each linked node $j$. Let $b_i(g, \phi)$ be the centrality of $i$ in network $g$. $B(g, \phi)$ the total centrality in network $g$ (i.e. $B(g, \phi) = \ell_n M \alpha$) and $B(g^{[-i]}, \phi) = \ell_{n-1} M^{[-i]} \alpha^{[-i]}$ the total centrality in $g^{[-i]}$, where $\alpha^{[-i]}$ is a $(n-1) \times 1$ column vector in which $\alpha_i$ have been removed and $M^{[-i]} = (I - \phi G^{[-i]})^{-1}$ is a $(n-1) \times (n-1)$ matrix in which the $i$th row and $i$th column corresponding to $i$ has been removed from $M$. Finally, let $\alpha[i]$ be a $(n \times 1)$ column vector where all entries but $i$ are defined as $\alpha[i]$, while entry $i$ contains the initial $\alpha_i$, and let $M[i]$ be the $n \times n$ matrix such that each element is $m_{jk} = \frac{m_{ij} m_{ik}}{m_{ii}}$ so that $B(g[i], \phi) = \ell_n M \alpha[i]$ and $\ell_n M[i] \alpha[i] = b_{\alpha[i],i}(g, \phi) \sum_{j=1}^{n} m_{ji}(g, \phi)/m_{ii}(g, \phi)$. Ballester and Zenou (2014) have proposed the following definition:

**Definition 3** For all networks $g$ and for all $i$, the intercentrality measure of delinquent $i$ is:

$$d_i(g, \phi) = B(g, \phi) - B(g^{[-i]}, \phi)$$

$$= \ell_n M \alpha - \ell_n M \alpha[i] + \ell_n M[i] \alpha[i]$$

$$= B(g, \phi) - B(g^{[i]}, \phi) + \frac{b_{\alpha[i],i}(g, \phi) \sum_{j=1}^{n} m_{ji}(g, \phi)}{m_{ii}(g, \phi)}.$$  \hspace{1cm} (17)

In this context, we have the following result due to Ballester et al. (2006, 2010) and Ballester and Zenou (2014).

**Proposition 4** A player $i^{*}$ is the key player if and only if $i^{*}$ is a delinquent with the highest intercentrality in $g$, that is, $d_i^{*}(g, \phi) \geq d_i(g, \phi)$, for all $i = 1, ..., n$.

A.2 Dynamic network formation: Theory

So far, we have assumed that the network was fixed and that, when a delinquent was removed, no new links were formed. In other words, we have an invariant assumption on the reduced network $g^{[-i]}$. We would like, now, to develop a dynamic model that extends the key-player approach proposed by Ballester et al. (2006, 2010) and exposed in Section 3.2. We first present a dynamic formation model and then analyze the key-player policy within this framework.

A.2.1 The dynamic model

We would like, now, to develop a dynamic model where both network formation and effort decisions take place. As we will see below (Section 4), in our dataset, we only observe the network at one point in time. This will correspond to our network at $t = 0$ and to the initial condition of our dynamic network formation process. We will analyze how the network will evolve over time both with and without a key player policy. What will change after $t = 0$ is the structure of the network as well as the crime effort each criminal will provide.
Let us now describe this dynamic model. At each period in time $t$, we consider a two-stage (morning-afternoon) game, with the timing of the game given as follows.

In the morning of day $t$, with equal probability, an agent (say, agent $i$) is chosen and makes a link-formation decision under uncertainty as he/she does not know the realization of a random shock $\varepsilon_i$ in utility (2). The shock is individual specific and i.i.d. across individuals such that $E(\varepsilon_i) = 0$ and $\text{Var}(\varepsilon_i) = \sigma_i^2 > 0$. The chosen agent can choose to nominate a new friend or keep the status quo but is not allowed to delete an existing link. We assume that the agent $i$ who initiates a friendship relationship with agent $j$ pays the link-formation cost $c_i$ and that he/she is myopic, i.e. agent $i$ only maximizes expected utility at the end of day $t$.

At noon of day $t$, a new network is formed, which is denoted by $g_t = g_t^{(i,j)}$ with the adjacency matrix $G_t = G_t^{(i,j)}$. If $j \neq i$, then $G_t^{(i,j)} = G_{t-1} + e_i e_j'$, where $e_i$ is the $i$th column of the identity matrix. If $j = i$, then $G_t^{(i,i)} = G_{t-1}$.

In the afternoon of day $t$, the random shock $\varepsilon_i$ in utility (2) is realized and its value becomes complete information for all agents. As in Section 3.1, all agents in the (new) network simultaneously choose their effort level to maximize their utility at time $t$. In particular, agent $i$ will choose an effort level $y_{i,t} \equiv y_{i,t}(g_t^{(i,j)})$ to maximize the utility

$$u_{i,t}(y_{i,t}, g_t^{(i,j)}) = (\pi_i + \eta + \varepsilon_i)y_{i,t} - \frac{1}{2}y_{i,t}^2 + \phi \sum_{k=1}^n g_{i,k,t}y_{i,t}y_{k,t} - c_i(y_{i,t} - \bar{g}_{i,t-1})$$

where $\bar{g}_{i,t} = \sum_{k=1}^n g_{i,k,t}$ and $c_i$ is the marginal cost of a link.

For each period in time $t$, we solve the model backwards, as usual. As in section 3.1, the unique Nash equilibrium of the “afternoon game” (assuming that $\phi_{M_i}(G_t(i,j)) < 1$) is such that

$$y_{i,t}^* = \phi \sum_{k=1}^n g_{i,k,t}y_{i,t}^* + \pi_i + \eta + \varepsilon_i$$

or in vector form $y_t^* = (I - \phi G_t)^{-1}(\pi + \eta l_n + \epsilon)$. Let $M_i \equiv M_i^{(i,j)} = (I - \phi G_t^{(i,j)})^{-1}$, with $m_{i,j,t} \equiv m_{i,j,t}^{(i,j)}$ being $M_i$'s $i$th row and $m_{i,j,t} \equiv m_{i,j,t}^{(i,j)}$ being its $(i,j)$th entry. Then $y_{i,t}^* = m_{i,t}(\pi + \eta l_n + \epsilon)$.

For the “morning game”, as $\epsilon$ is unobservable in the morning, the chosen agent $i$ makes his/her

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42 If we allow individuals to delete links so that they delete links with the individuals that reduce their utility the least, then, as in König et al. (2014), the Markov chain will be ergodic and the unique steady state network will be a nested-plit graph. These types of networks, which are nested and disassortative, match well bank or trade networks but do not fit well friendship networks (such as the ones in our dataset) that tend to be assortative (i.e. homophily behavior tend to prevail). This is why, in our framework, individuals do not sever links but can still not have as many friends as they want because of the cost of forming links, which increases with the number of links.

43 The assumption of selecting one individual at a time is standard in the dynamic network formation literature (see e.g. König et al., 2014) because, otherwise, it would be impossible to characterize the equilibria given the standard coordination problems prevalent in strategic network formation (see e.g. Jackson, 2008, chap. 6). The assumption of myopic behavior is also standard in this literature because of the numerous possible networks that can be formed in the future (for $n$ players, there are $2^{n(n-1)/2}$ possible networks that can be formed). Observe, however, that, in our model, where agents form links to the most central agents, then assuming that agents will form links based on their discounted life time expected utility (forward-looking agents), instead of current utility, will not change the main results since they will still form links with the agent who has the highest Katz-Bonacich centrality in the network. This is because this agent has a higher probability than any other agent in the network to have the highest Katz-Bonacich centrality in the future (at any period in time). In other words, there exists a farsighted equilibrium which has the same properties as ours. In the simulation exercises (Section 6.1), we look at both myopic and forward-looking behavior and find the same results for the key-player policy.
Let \( \gamma \) be the network obtained from \( \gamma_{1,t} \) by adding the edge \( ij \) between agents \( i,j \in N \).

Using (21), the inequality (22) gives the lower bound of \( c_i \):

\[
\kappa_{i,t}(g_{t}^{(i,j)}) = \frac{1}{2}[E[u_{i,t}(y_{t}^{*},g_{t}^{(i,j)})]]^2 + \sigma_i^2 m_{i,t}^{(i,j)} - \frac{1}{2} \sigma^2 m_{i,t}^{(i,j)} + \phi \sigma^2 \sum_{k=1}^{n} g_{k,t} m_{i,t}^{(i,j)} m_{k,t}^{(i,j)}. 
\]

Using (21), the inequality (22) gives the lower bound of \( c_i \):

\[
\varphi_{i,t} = \max_{j} \kappa_{i,t}(g_{t}^{(i,j)}) - \kappa_{i,t}(g_{t}^{(i,j)}),
\]

such that if \( c_i \geq \varphi_{i,t} \) then agent \( i \) will have no incentive to create a new link at period \( t \).

Let us now determine the convergence and the equilibrium of this dynamic formation model. Let time be measured at countable dates \( t = 0, 1, 2, \ldots \) and consider a discrete time Markov chain for the network formation process \( (g_t)_{t=0}^{\infty} \) with \( g_t = (N,L_t) \) comprising the set of delinquents \( N = \{1,\ldots,n\} \) together with a set of links \( L_t \) at time \( t \) between them. \( (g_t)_{t=0}^{\infty} \) is a collection of random variables \( g_t \), indexed by time \( t \) on a probability space \( (\Omega,\mathcal{F},\mathbb{P}) \), where \( \Omega \) is the countable state space of all networks with \( n \) nodes, \( \mathcal{F} \) is the \( \sigma \)-algebra \( \sigma\{g_t: t = 0, 1, 2, \ldots\} \) generated by the collection of \( g_t \), and \( \mathbb{P} : \mathcal{F} \to [0, 1] \) is a countably additive, non-negative measure on \( (\Omega,\mathcal{F}) \) with total mass \( \sum_{g \in \Omega} \mathbb{P}(g) = 1 \). At every time \( t \geq 0 \), links can be created, or not, according to the game described above.

**Definition 5** Consider a discrete time Markov chain \( (g_t)_{t=0}^{\infty} \) on the probability space \( (\Omega,\mathcal{F},\mathbb{P}) \). Consider a network \( g_t = (N,L_t) \) at time \( t \) with delinquents \( N = \{1,\ldots,n\} \) and links \( L_t \). Let \( g_t^{(i,j)} \) be the network obtained from \( g_{t-1} \) by the addition of the edge \( ij \in L_{t-1} \) between agents \( i,j \in N \). Let \( u_t(y_t^{*},g_t) = (u_{1,t}(y_t^{*},g_t),\ldots,u_{n,t}(y_t^{*},g_t)) \) denote the profile of Nash equilibrium payoffs of the
delinquents in \( g_t \) following from the payoff function (18) with parameter \( \phi < 1/\mu_1(G_t) \). Then the delinquent \( j \) is a best response of delinquent \( i \) if \( u_{i,t}(y_t^i, g_t^{(i,j)}) \geq u_{i,t}(y_t^i, g_t^{(i,k)}) \) for all \( k \in N \setminus N_{i,t-1} \), where \( N_{i,t} = \{ j \in N : ij \in L_t \} \) is the neighborhood of individual \( i \in N \) at \( t \). The set of delinquent \( i \)'s best responses is denoted by \( BR_{i,t} \).

The key question is how individuals choose among their potential linking partners. This definition shows that, at every \( t \), an agent \( i \), selected uniformly at random from the set \( N \), enjoys an opportunity of updating his/her current links. If an agent \( i \) receives such an opportunity, then he/she initiates a link to agent \( j \) which increases his/her equilibrium payoff the most. Agent \( j \) is said to be the best response of agent \( i \) given the network \( g_t \). In our framework, agent \( j \) always accepts the link proposal because he/she does not pay the cost of the link and his/her utility always increases following the creation of the link because of local complementarities. If the utility of not creating a link is higher than that of creating a link with individual \( i \)'s best response, then a link is not created and the network is unchanged.

**Definition 6** We define the network formation process \( (g_t)_{t=0}^{\infty} \) with \( g_0 = (N, L_0) \), as a sequence of networks \( g_0, g_1, \ldots \) in which, at every time \( t = 0, 1, 2, \ldots \), a delinquent \( i \in N \) is uniformly selected at random. This delinquent \( i \) initiates a link to a best response delinquent \( j \in BR_{i,t} \). The link is created if \( BR_{i,t} \neq \emptyset \) and \( u_{i,t}(y_t^i, g_t^{(i,j)}) \geq u_{i,t}(y_t^i, g_t^{(i,i)}) \). No link will be created otherwise. If \( BR_{i,t} \) is not unique, then \( i \) randomly selects one delinquent in \( BR_{i,t} \).

In this framework, the newly established link affects the overall network structure and thus the centralities and payoffs of all other delinquents in the network. The formation of links can thus introduce large, unintended and uncompensated externalities.

We now analyze the network formation process \( (g_t)_{t=0}^{\infty} \) defined above, in more detail, where \( g_t \) is the random variable realized at time \( t \geq 0 \). Let us show that the network formation process \( (g_t)_{t=0}^{\infty} \) introduced in Definition 6 induces a Markov chain on a finite state space \( \Omega \). \( \Omega \) contains all unlabeled graphs with \( n \) nodes. Therefore, the number of states is finite and the transition between states can be represented with a transition matrix \( T \). Let us show that \( (g_t)_{t=0}^{\infty} \) is a Markov chain. The network \( g_{t+1} \) is obtained from \( g_t \) by adding a link to \( L_t \) or doing nothing. Thus, the probability of obtaining \( g_{t+1} \) depends only on \( g_t \) and not on the previous networks \( g_t \) for \( t' < t \), that is

\[
P(g_{t+1}|g_0, g_1, \ldots, g_t) = P(g_{t+1}|g_t).
\]

The number of possible networks \( g_t \) is finite for any time \( t \) and the transition probability from a network \( g_t \) to \( g_{t+1} \) does not depend on \( t \). Therefore, \( (g_t)_{t=0}^{\infty} \) is a finite, discrete time, homogeneous Markov chain. Moreover, the transition matrix \( T = [T_{ij}] \) is defined by

\[
T_{ij} = P(g_{t+1} = g_j \mid g_t = g_i) \text{ for any } g_i, g_j \in \Omega.
\]

Let us explain what kind of equilibrium concept we are using for this dynamic network formation model. As above, define \( E[u_{i,t}(y_t^i, g_t^{(i,j)})] \) is the expected utility at time \( t \) for \( i \) to create a link with
\[
\text{Definition 7} \quad \text{Consider the network formation process } (g_t)_{t=0}^\infty \text{ with } g_t = (N, L_t) \text{ described in Definition 6, where, at each period in time } t, \text{ the morning-afternoon game described in Section A.2.1 is played. We say that the network } g_0 \text{ at time } t = 0 \text{ converges to an equilibrium network } g_T \text{ at time } t = T \text{ when each of the } n \text{ delinquents in the network } g_T \text{ has no incentive to create a new link at time } t = T, \text{ that is, } E[u_{i,t}(y_t^i, g_{t}^{(i,j)})] > \max_j E[u_{i,T}(y_t^i, g_{t}^{(i,j)})] \text{ for all } i = 1, \ldots, n.
\]

This definition says that the first time period for which each delinquent has no incentive to create a new link is \( T \). This means that at times \( T + 1, T + 2, \) etc., there are also no incentives for them to create a new link. In that case, the network \( g_T = (N, L_T) \) is an equilibrium network. In terms of Markov chain, this means that the equilibrium network \( g_T \) is an absorbing state. From now on, when use the word “equilibrium” or “equilibrium network” in the dynamic network formation model, we refer to the equilibrium concept defined in Definition 7.

Observe that the discrete time Markov chain is not ergodic (since it is not irreductible) and thus the absorbing state a network will converge to will strongly depend on the initial network \( G_0 \). In the empirical implementation of this model, the initial condition \( G_0 \) will be determined by the network we observe in the data.

Presumably the Markov chain has multiple (and potentially many) absorbing states. Depending on the order through which agents are picked, the system might end up in very different states. However, since we mainly use the dynamic model to determine how the network changes when the key player is removed and since we start at an absorbing state, i.e. at an equilibrium network where no agent has an incentive to form a link, the convergence to a new absorbing state after the removal of the key player is very quick. Given that the networks in our data set are small, in the simulations of the dynamic model performed in Section 6.1, we show that the convergence is extremely fast and that it does not depend on which agent is chosen first to form a link. In other words, using data-based simulations, we show that, whoever the first agent is picked, there is only one absorbing steady-state in each network after the removal of the key player.

A.2.2 Finding the key player in the dynamic model

We will now implement a key-player policy in the dynamic network formation model. At \( t = 0 \), before the dynamic network formation game described above starts, the planner will choose the key player \( i^* \) in the following way.\(^{44}\) The planner will compare the (expected) total crime that will emerge in equilibrium (Definition 7) when he/she removes different delinquents from the network. As in Section 3.2, the key player \( i^* \) will be the delinquent whose removal leads to the lowest total expected crime in the equilibrium network.

\(^{44}\) We assume that, after the removal of the key player, a random person in the network initiates the search for new links. One could argue that, following the arrest of a crime leader, it is his/her closest associates that initiate the search for new links. Doing so will in fact not change any of our results in the simulation exercises (see Section 6.1). Indeed, even if we choose a person at random, we reach an equilibrium only when nobody in the network wants to form a link, including the closest associate of a crime leader. This is mainly because the networks are relatively small and we start from an equilibrium situation (nobody in the network wants to form a link) and move to another equilibrium situation (where after removing the key player nobody in the network wants to form a link).
Let us now calculate the total expected crime of the equilibrium network after removing a delinquent at \( t = 0 \). Let the adjacency matrix for the equilibrium network \( g_T^{-i} \) without delinquent \( i \) be denoted by \( G_T^{-i} \). In that case, the expected equilibrium effort outcome is equal to:

\[
E[y_T^i(g_T^{-i})] = (I - \phi G_T^{-i})^{-1} (\pi^{-i} + \eta l_{n-1}).
\]

Then the total expected crime for the equilibrium network is: \( \sum_{j=1,j\neq i}^n E[y_{j,T}^i(g_T^{-i})] \).

The planner’s objective is to find the delinquent whose removal leads to the lowest total expected crime in the equilibrium network. Formally, the planner’s problem is:

\[
\min \left\{ \sum_{j=1,j\neq i}^n E[y_{j,T}^i(g_T^{-i})] \mid i = 1, \ldots, n \right\}.
\]

(25)

A.3 Dynamic network formation and key player: Econometric issues

To simplify notation, we drop the subscript \( r \) when there is no ambiguity. To determine the key player, we first need to estimate the total expected crime in equilibrium when a delinquent is removed, i.e., \( \sum_{j=1,j\neq i}^n E[y_{j,T}^i(g_T^{-i})] \). Remember that the expected equilibrium crime effort when \( i \) has been removed is given by \( E[y_T^i(g_T^{-i})] = (I_{n-1} - \phi G_T^{-i})^{-1} (\tilde{X}^{-i} \beta + \eta l_{n-1}) \) and \( \bar{E}[y_{i,T}^i(g_T^{-i})] \) is the sum of each element of the vector \( E[y_T^i(g_T^{-i})] \). We estimate \( E[y_T^i(g_T^{-i})] \) as

\[
E[y_T^i(g_T^{-i})] = (I_{n-1} - \hat{\phi} G_T^{-i})^{-1} (\tilde{X}^{-i} \hat{\beta} + \hat{\eta} l_{n-1}),
\]

(26)

where \( \hat{\phi} \) and \( \hat{\beta} \) are the estimates obtained from the bias-corrected many-IV GMM estimation procedure in Section 5, and \( \eta \) can be estimated by the average of the estimation residuals. The only parameter that is not estimated from the bias-corrected many-IV GMM estimation is \( c_i \), the marginal cost of forming links. Let us assume that the network observed in the AddHealth data is in equilibrium \( (t = 0) \), as per Definition 7, that is, no one has an incentive to create a new link at day \( t = 1 \), and denote this network by \( G_0 \) (i.e. the adjacency matrix at day \( t = 0 \)). For each \( i \), \( \zeta \) is defined by (24).

Let \( \tilde{M}^{(i,j)}_t = (I - \hat{\phi} G^{(i,j)}_t)^{-1} \), with \( \tilde{m}^{(i,j)}_{t,i} \) being \( \tilde{M}^{(i,j)}_t \)'s \( i \)th row and \( \tilde{m}^{(i,j)}_{t,i} \) being its \((i,j)\)th entry. As \( E(y_{i,t}^i) = \tilde{m}^{(i,j)}_{t,i} (\tilde{X} \hat{\beta} + \hat{\eta} l_{n}) \), from (23) \( \kappa_{i,t}(g_{t}^{(i,j)}) \) can be estimated by:

\[
\hat{\kappa}_{i,t}(g_{t}^{(i,j)}) = 1/2 \tilde{m}^{(i,j)}_{t,i} (\tilde{X} \hat{\beta} + \hat{\eta} l_{n})^2 + \tilde{\sigma}^2 \tilde{m}^{(i,j)}_{t,i} \tilde{m}^{(i,j)}_{t,i} + \tilde{\phi} \tilde{\sigma}^2 \sum_{k=1}^n g_{k,i}^{(i,j)} \tilde{m}^{(i,j)}_{k,i} \tilde{m}^{(i,j)}_{k,i}.
\]

Hence, in the simulations, we estimate \( \zeta \) by

\[
\tilde{\zeta} = \max_j \hat{\kappa}_{i,1}(g_1^{(i,j)}) - \hat{\kappa}_{i,1}(g_1^{(i,i)}).
\]

(27)

Observe that even if \( c_i = \zeta \) for all \( i \) so that nobody will want to form a link, it will be possible that links will be formed after the removal of the key player since \( \zeta(g) \neq \zeta(g_i^{-i}) \).
We will compare the determination of the key player that solves (25), i.e.

$$\min_i \left\{ \sum_{j=1, j \neq i}^n E[y_{j,T}^{(g_{T}^{[-i]})}] \mid i = 1, \ldots, n \right\}$$

with the key player calculated in the invariant case, i.e. the network is given and there is no link formation. To be consistent with (25), in the invariant network case, we will calculate the key player as the one whose removal leads to the largest expected total crime reduction\(^4\), or equivalently, the key player \(i^*\) will be the one that solves:

$$\min_i \left\{ \sum_{j=1, j \neq i}^n E[y_{j,0}^{(g_{0}^{[-i]})}] \mid i = 1, \ldots, n \right\}$$

(28)

B Data appendix

[Insert Tables A1 and A2 here]

C Identification of the local-aggregate model

Let

$$\Lambda_1 = \begin{bmatrix} \beta_2 c_1 & 1 & -\phi_1 c_1 \\ \beta_1 + \beta_2 c_2 & -\phi_1 & -\phi_1 c_2 \\ \beta_2 c_3 & 0 & 1 - \phi_1 c_3 \\ \eta_r & 0 & 0 \end{bmatrix}$$

(29)

and

$$\Lambda_2 = \begin{bmatrix} -\beta_2 c_1 & 1 & \phi_1 c_1 \\ \beta_1 - \beta_2 c_2 & -\phi_1 & \phi_1 c_2 \\ -\beta_2 c_3 & 0 & \phi_1 c_3 + 1 \\ -\beta_2 c_5 & 0 & \phi_1 c_5 - 1 \end{bmatrix}$$

(30)

Proof of Proposition 2. We follow the identification strategy as in Bramoullé et al. (2009) by investigating identification conditions which can be revealed via networks as functions on a vector of regressors to outcomes. Thus, we assume \(X_r\) is a vector in this proof. First, we consider the case that, for some network \(r\), \(G_r\) has non-constant row sums. In this case, \(E(JZ) = J[E(Gy), X, G^*X]\) has full column rank if

$$J_r[E(G_r y_r)d_1 + X_r d_2 + G_r^* X_r d_3] = 0$$

(31)

implies \(d_1 = d_2 = d_3 = 0\). As \(J_r = I_{n_r} - \frac{1}{n_r} l_{n_r} l_{n_r}'\), (31) can be rewritten as

$$E(G_r y_r)d_1 + X_r d_2 + G_r^* X_r d_3 + l_{n_r} \mu = 0,$$

(32)

Note this is different from the definition of the key player in Section 3.2.
where \( \mu = -\frac{1}{m} l'_{n_r} [E(G_r y_r) d_1 + X_r d_2 + G_r^* X_r d_3] \). As

\[
(I_{n_r} - \phi_1 G_r) E(G_r y_r) = G_r X_r \beta_1 + G_r G_r^* X_r \beta_2 + G_r l_{n_r} \eta_r
\]

from the reduced form equation, premultiplying (32) by \((I_{n_r} - \phi_1 G_r)\) gives

\[
X_r d_2 + G_r X_r (\beta_1 d_1 - \phi_1 d_2) + G_r^* X_r d_3 + G_r G_r^* X_r \beta_2 d_1 - \phi_1 d_2) + l_{n_r} \mu + G_r l_{n_r} (\eta_r d_1 - \phi_1 \mu) = 0.
\]

Note, as \( G_r = R_r G_r^* \), where \( R_r \) is a diagonal matrix with the \( i \)th diagonal element being \( \bar{g}_{i,r} = \sum_j g_{i,j,r} \). \( G_r, G_r^* \) are linearly independent if and only if rows sums of \( G_r \) are not constant. For \( G_r \) with non-constant row sums, we consider two cases. (i) \( I_{n_r}, G_r, G_r^*, G_r^* \) are linearly independent. In this case, \([X_r, G_r X_r, G_r^* X_r, G_r G_r^* X_r, l_{n_r}, l_{n_r}]\) has full column rank. Thus, for a general \( X_r \), \([X_r, G_r X_r, G_r^* X_r, G_r G_r^* X_r, l_{n_r}, l_{n_r}]\) has full column rank, which implies \( d_2 = \beta_1 d_1 - \phi_1 d_2 = d_3 = \beta_2 d_1 - \phi_1 d_3 = \mu = \eta_r d_1 - \phi_1 \mu = 0 \). Therefore, \( d_1 = d_2 = d_3 = 0 \) if \( \beta_1, \beta_2, \eta_r \) are not all zeros. (ii) \( G_r G_r^* = c_1 I_{n_r} + c_2 G_r + c_3 G_r^* \) for some constant scalars \( c_1, c_2, c_3 \). In this case,

\[
0 = X_r (\beta_2 c_1 d_1 + d_2 - \phi_1 c_1 d_3) + G_r X_r (\beta_1 + \beta_2 c_2) d_1 - \phi_1 d_2 - \phi_1 c_2 d_3) + G_r^* X_r (\beta_2 c_3 d_1 + (1 - \phi_1 c_3) d_3) + l_{n_r} \mu + G_r l_{n_r} (\eta_r d_1 - \phi_1 \mu),
\]

which implies \( d_1 = d_2 = d_3 = 0 \) if \( A_1 \) given by (29) has full rank. When \( \eta_r \neq 0 \), a sufficient condition for \( A_1 \) to have full rank is \( |\phi_1 c_1 + c_2| + |1 - \phi_1 c_3| \neq 0 \).

Next, consider the case that \( G_r \) has constant row sums such that \( \bar{g}_{i,r} = \bar{g}_r \) for all \( r \). In this case, \( G_r = g_r G_r^* \). \( E(JZ) = J [E(G y) X, G^* X] \) has full column rank if

\[
J [E(G y) d_1 + X d_2 + G^* X d_3] = 0
\]

implies \( d_1 = d_2 = d_3 = 0 \). As \( J (I - \phi_1 G)^{-1} G L = 0 \), substitution of \( E(G y) = (I - \phi_1 G)^{-1} (G X \beta_1 + G G^* X \beta_2 + G L \eta) \) into (33) gives

\[
J (I - \phi_1 G)^{-1} [X d_2 + G X (\beta_1 d_1 - \phi_1 d_2) + G^* X d_3 + G G^* X (\beta_2 d_1 - \phi_1 d_3)] = 0,
\]

which implies

\[
X d_2 + G X (\beta_1 d_1 - \phi_1 d_2) + G^* X d_3 + G G^* X (\beta_2 d_1 - \phi_1 d_3) = c L
\]

because \( J L = 0 \). As \( G^* L = L \), premultiplying (34) by \( G^* \) gives

\[
G^* X d_2 + G G^* X (\beta_1 d_1 - \phi_1 d_2) + G^2 X d_3 + G G^2 X (\beta_2 d_1 - \phi_1 d_3) = c L.
\]

From (34) and (35), when \( I, G, G^*, GG^*, G^2, GG^2 \) are linearly independent, \( d_1 = d_2 = d_3 = 0 \) if \( \beta_1, \beta_2 \) are not both zeros. When \( GG^2 = c_1 I + c_2 G + c_3 G^* + c_4 G G^* + c_5 G^2 \) and \( I, G, G^*, GG^*, G^2 \) are linearly independent, \( d_1 = d_2 = d_3 = 0 \) if \( A_2 \) given by (30) has full rank. On the other hand, if \( \bar{g}_r = \bar{g} \) for all \( r \), then \( G = g G^* \). When \( I, G^*, G^2, G^3 \) are linearly independent, (34) and (35)
imply $d_1 = d_2 = d_3 = 0$ if $\phi_1 \beta_1 + \beta_2 \neq 0$. ■

D Estimation of the local-aggregate model

D.1 The 2SLS estimator

In this paper, we estimate (11) using the 2SLS and generalized method of moments (GMM) approaches proposed by Liu and Lee (2010). The conventional instruments for the estimation of (11) are $Q_1 = [J X, G^* X, GX, GG^* X]$ (finite-IV 2SLS). For the local-aggregate model, Liu and Lee (2010) have proposed to include additional instruments $J GL$ so that $Q_2 = [Q_1, J GL]$ (many-IV 2SLS). The additional instruments $J GL$ are based on the leading-order term of the Katz-Bonacich centrality. Those additional IVs could help model identification when the conventional IVs are weak and improve upon the estimation efficiency of the conventional 2SLS estimator based on $Q_1$. As $J GL$ has $\bar{r}$ columns, the number of instruments will increase with the sample size $n$ if the number of networks $\bar{r}$ increases with $n$. Therefore, the 2SLS using $Q_2$ could be asymptotically biased when $\bar{r}$ increases too fast relative to $n$ (see, e.g., Bekker, 1994; Bekker and van der Ploeg, 2005; Hansen et al., 2008). Liu and Lee (2010) have shown that the many-IV 2SLS estimator has a properly-centered asymptotic normal distribution when the average group size is large relative to the number of networks in the sample. Liu and Lee (2010) have proposed a bias-correction procedure based on the estimated leading-order many-instrument bias. The bias-corrected 2SLS is properly centered, asymptotically normally distributed, and efficient when the average group size is sufficiently large.

To summarize, the 2SLS estimators of $\theta = (\phi, \beta_1', \beta_2')'$ considered in the empirical studies of this paper are:

(i) **Finite-IV 2SLS**: $\hat{\theta}_{2sls-1} = (Z'P_1 Z)^{-1} Z' P_1 y$, where $P_1 = Q_1 (Q_1^* Q_1)^{-1} Q_1^*$ and $Q_1$ contains the linearly independent columns of $[JX, G^* X, GX, GG^* X]$.

(ii) **Many-IV 2SLS**: $\hat{\theta}_{2sls-2} = (Z'P_2 Z)^{-1} Z' P_2 y$, where $P_2 = Q_2 (Q_2^* Q_2)^{-1} Q_2^*$ and $Q_2$ contains the linearly independent columns of $[Q_1, J GL]$.

(iii) **Bias-corrected 2SLS**: $\hat{\theta}_{bias-corr} = (Z'P_2 Z)^{-1} [Z' P_2 y - \bar{d}^2 \text{tr}(P_2 G \tilde{M}) e_1]$, where $\tilde{M} = (I - \tilde{\phi} G)^{-1}$, and $\bar{d}^2, \tilde{\phi}$ are $\sqrt{\pi}$-consistent initial estimators of $\sigma^2, \phi$.

D.2 The GMM estimator

The 2SLS approach can be generalized to the GMM with additional quadratic moment equations. While the IV moments use the information of the mean of the reduced-form equation for estimation, the quadratic moments explore the correlation structure of the reduced-form disturbances. Liu and Lee (2010) have shown that the many-IV GMM estimators can be consistent, asymptotically normal, and efficient when the sample size grows fast enough relative to the number of networks. Liu and Lee (2010) have also suggested a bias-correction procedure for the many-IV GMM estimator based on the estimated leading order many-instrument bias. The bias-corrected GMM is shown to be more efficient than the corresponding 2SLS estimator.

Let $M = (I - \phi G)^{-1}, U = J GM J - \text{tr}(J GM J)/\text{tr}(J)$ and $e(\theta) = J (y - Z \theta)$. To summarize, the GMM estimators of $\theta = (\phi, \beta_1', \beta_2')'$ considered in the empirical studies of this paper are:

(i) **Finite-IV GMM**: $\hat{\theta}_{gm-1}$ is the (feasible) optimal GMM estimator with moment conditions $g_1(\theta) = [Q_1, U e(\theta)]' e(\theta)$, and $Q_1$ is constructed as in the finite-IV 2SLS.
(ii) Many-IV GMM: $\hat{\theta}_{gmm-2}$ is the (feasible) optimal GMM estimator with moment conditions $g_2(\theta) = [Q_2, Ue(\theta)]'e(\theta)$, and $Q_2$ is constructed as in the many-IV 2SLS.

(iii) Bias-corrected GMM: $\hat{\theta}_{cgmm-2} = \hat{\theta}_{gmm-2} - \tilde{b}_{gmm}$, where $\tilde{b}_{gmm}$ is the estimated leading-order many-instrument bias given in Liu and Lee (2010).

D.3 The OIR test

Our identification strategy and the validity of the moment conditions employed by the 2SLS and GMM estimators rest on the exogeneity of the adjacency matrix $G$ (conditional on covariates and network fixed effects). We test the exogeneity of $G$ using the over-identifying restrictions (OIR) test. If the OIR test cannot reject the null hypothesis that the moment conditions are correctly specified, then it provides evidence that $G$ is exogenous. If the number of moment restrictions is fixed, the OIR test statistic given by the 2SLS (or GMM) objective function evaluated at the 2SLS (or GMM) estimator follows a chi-squared distribution with degrees of freedom equal to the number of over-identifying restrictions (Lee, 2007b, Proposition 2). However, the OIR test might not be robust in the presence of a large number of moment restrictions. Hence, we only consider the OIR test for the 2SLS and GMM estimator based on IV matrix $Q_1$.

E Robustness checks

E.1 Estimation of the local-aggregate model with endogenous crime participation

Without loss of generality, we assume the first $\bar{n}$ (of the $n$) individuals will choose to become criminals. For those who become criminals, $y_i^* = X_1 \gamma + \epsilon_1$, where $y_i^* = (y_{i,1}^*, \ldots, y_{i,n_i}^*)' > 0$, $X_1 = (x_{1,1}, \ldots, x_{n_i})'$ and $\epsilon_1 = (\epsilon_{1,1}, \ldots, \epsilon_{n_i})'$, and their crime effort levels in vector form are given by (10), i.e.,

$$y = \phi Gy + X_1 \beta_1 + G^* X_2 \beta_2 + L\eta + \epsilon_2,$$

where $y = (y_1, \ldots, y_n)'$, $X = (x_1, \ldots, x_n)'$ and $\epsilon_2 = (\epsilon_{1,2}, \ldots, \epsilon_{n,2})'$. Let $M = (I - \phi G)^{-1}$ and the $i$th row of $M$ be $m_i$. Then, from the reduced form equation of (36), we have $y_i = m_i (X_1 \beta_1 + G^* X_2 \beta_2 + L\eta) + m_i \epsilon_2$. Given the participation decisions of the $\bar{n}$ individuals in the first stage, the expected crime effort of criminal $i$ is equal to:

$$E[y_i|y_i^* > 0] = m_i (X_1 \beta_1 + G^* X_2 \beta_2 + L\eta) + m_i E[\epsilon_2|\epsilon_1 > -X_1 \gamma]$$

The term $E[\epsilon_2|\epsilon_1 > -X_1 \gamma]$ is the correction term for the sample-selection bias.

Suppose, for $i, j = 1, \ldots, n$,

$$\begin{bmatrix} \epsilon_{i,1} \\ \epsilon_{i,2} \end{bmatrix} \sim N \left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix} \right),$$

46 For the case with independent observations, Chao et al. (2010) have proposed an OIR test that is robust to many IVs. However, no robust OIR test with many IVs is available when observations are spatially correlated.
and $E(\epsilon_i | \epsilon_j) = 0$ for $i \neq j$. Then, $E[\epsilon_2 | \epsilon_1 > -X_1 \gamma] = \sigma_{12} \lambda$, where $\lambda = [\lambda(x'_{1,1} \gamma), ..., \lambda(x'_{n,1} \gamma)]'$ and $\lambda(x'_{i,1} \gamma) = \phi (x'_{i,1} \gamma) / \phi (x'_{1,1} \gamma)$. Substitution of $\sigma_{12} \lambda$ into (37) gives, in matrix notation,

$$E[y | y^* > 0] = M(X_2 \beta_1 + G'X_2 \beta_2 + L \eta) + \sigma_{12} M \lambda. \quad (38)$$

From (38), the infeasible selection-bias-corrected outcome equation is given by

$$y = \phi G y + X_1 \beta_1 + G'X_2 \beta_2 + L \eta + \sigma_{12} \lambda + \epsilon^*,$$

where $\epsilon^* = \epsilon_2 - \sigma_{12} \lambda$ is the bias-corrected error term such that $E[\epsilon^* | y^*_1 > 0] = 0$. The conditional variance of $\epsilon^*$ is $\text{Var}(\epsilon^* | y^*_1 > 0) = \sigma_2^2 I - \sigma_{12} \sigma_{12}$. Where $A = \text{diag}(\lambda(x'_{1,1} \gamma) x_{1,1} \gamma + \lambda^2(x'_{1,1} \gamma))_i$.

The selection-bias-corrected outcome equation can be estimated following Heckman’s two-step approach. In the first step, we estimate $\gamma$ in the participation equation (15) using the probit maximum likelihood estimator $\hat{\gamma}$. With estimated inverse Mills ratios $\hat{\lambda} = [\lambda(x'_{1,1} \hat{\gamma}), ..., \lambda(x'_{n,1} \hat{\gamma})]'$, the (feasible) selection-bias-corrected outcome equation is

$$y = \phi G y + X_1 \beta_1 + G'X_2 \beta_2 + L \eta + \sigma_{12} \hat{\lambda} + \epsilon, \quad (39)$$

where $\epsilon = \epsilon_2 - \sigma_{12} \hat{\lambda} = \epsilon^* - \sigma_{12}(\hat{\lambda} - \lambda)$. After we eliminate the fixed group effect by the projector $J$, (39) becomes

$$Jy = \phi JG y + JX_1 \beta_1 + JG'X_2 \beta_2 + \sigma_{12} J \hat{\lambda} + J \epsilon.$$

Let $Q = J[X, G'X, GX, G^2X, \lambda]$ be an (infeasible) IV matrix and $\hat{Q}' = J[X, G'X, GX, G^2X, \hat{\lambda}]$. Let $P = Q(\hat{Q}'Q)^{-1} \hat{Q}'$. $\hat{P} = \hat{Q}'(\hat{Q}' \hat{Q})^{-1} \hat{Q}'$, $Z = [Gy, X, G'X, \lambda]$, and $\hat{Z} = [Gy, X, G'X, \hat{\lambda}]$. Then the 2SLS estimator of $\theta = (\phi, \beta_1, \beta_2, \sigma_{12})'$ is given by $\hat{\theta} = (\hat{Z}' \hat{P} \hat{Z})^{-1} \hat{Z}' \hat{P} y$. As, by the mean value theorem,

$$\frac{1}{\sqrt{n}} \hat{Z}' \hat{P} \epsilon = \frac{1}{\sqrt{n}} \hat{Z}' \hat{P} [\epsilon^* - \sigma_{12}(\hat{\lambda} - \lambda)] = \frac{1}{\sqrt{n}} \hat{Z}' \hat{P} \epsilon^* - \sigma_{12} \frac{1}{\sqrt{n}} \hat{Z}' \hat{P} A(\gamma) X_1 (\hat{\gamma} - \gamma),$$

the asymptotic variance of $\hat{\theta}$ is

$$\text{Avar} \sqrt{n}(\hat{\theta} - \theta) = \text{Avar} \frac{1}{\sqrt{n}} \hat{Z}' \hat{P} \hat{Z})^{-1} \frac{1}{\sqrt{n}} \hat{Z}' \hat{P} \epsilon = \text{plim} \frac{1}{n} \hat{Z}' P Z)^{-1} \frac{1}{n} \hat{Z}' P Z, \quad (39)$$

where $\Sigma = \frac{1}{n} \hat{Z}' P [\sigma_2^2 I - \sigma_{12} A + \sigma_{12} A X_1 (X'_{1,1} A_{1,1} X_{1,1}^{-1}) X'_{1} A | P Z$ and $A_n = \text{diag}(\frac{\phi^2(x'_{i,1} \gamma)}{1 - \phi(x'_{i,1} \gamma)})_i.$

To estimate $\sigma_2^2$, we consider $E[\epsilon^* | y^*_1 > 0] = \sigma_2^2 I - \sigma_{12} A$. Let $\hat{\epsilon}^* = J y - J \hat{Z} \hat{\theta}$. Then $\sigma_2^2$ can be estimated by $\hat{\sigma}_2^2 = \hat{\epsilon}^* \hat{\epsilon}^*/\text{tr}(J) + \hat{\sigma}_{12}^2 \frac{1}{n} \sum_{i=1}^n [\lambda(x'_{1,1} \gamma) x'_{i,1} \gamma + \lambda^2(x'_{1,1} \gamma)].$

**E.2 Network misspecification issues**

[Insert Table A3 here]

---

47 As the selection-bias correction introduces heteroskedasticity to the error term, the asymptotic properties of the many-instrument 2SLS and GMM become very difficult to derive. Hence, we only use the “conventional” instruments, which are very informative as indicated by the first-stage partial F-statistic, to estimate the selection-bias-corrected model.
Figure 1: Example networks where the local-aggregate model can be identified

(a)  (b)  (c)

Figure 2: Distribution of networks by size

number of networks

network size
Figure 3: Who is the key player?

- **Dynamic network**
  - Key player is the most active
  - Key player has the highest betweenness centrality
  - Key players are the same for static and dynamic networks
- **Static network**
  - Key player is NOT the most active
  - Key player does NOT have the highest betweenness centrality
  - Key players are different for static and dynamic networks
Figure 4: Change in network topology after removal of the key player

Figure 4: Change in network topology from the static network to the dynamic network
Figure 5: Crime reduction and network size
Figure 6: Difference between different criminal-target policies

- average % crime reduction of the key-player policy
- average % crime reduction of the most-active-player policy
- average % crime reduction of the random-target policy

![Graph showing the difference between different criminal-target policies](image-url)
<table>
<thead>
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<th>Variable definition</th>
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<td><strong>Individual socio-demographic variables</strong></td>
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<td>Student grade</td>
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<td>Black or African American</td>
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<tr>
<td>Other races</td>
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<td>Physical development</td>
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<td><strong>Family background variables</strong></td>
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<td>Single parent family</td>
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<td>Parent occupation dummies</td>
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<td><strong>Protective factors</strong></td>
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<td>Relationship with teachers</td>
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<tr>
<td>Social inclusion</td>
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<td>Parental care</td>
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<tr>
<td><strong>Residential neighborhood variables</strong></td>
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<td>Residential building quality</td>
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<td>Residential area urban</td>
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<td><strong>Additional selection equation variables</strong></td>
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<td>Religion practice</td>
</tr>
<tr>
<td>Outside Options</td>
</tr>
</tbody>
</table>
Table A2: Summary statistics

<table>
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<tr>
<th>VARIABLES</th>
<th>Non criminals (population)</th>
<th>Criminals (population) N = 4,868</th>
<th>Criminals (selected sample) N = 1,297</th>
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<tbody>
<tr>
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<td>N = 6,993</td>
<td>Network size range 2-1,050</td>
<td>Network size range 4-150</td>
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<td></td>
<td></td>
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<td>sd</td>
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<td>0.31</td>
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<td>0.47</td>
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<td>Parent occupation military or security</td>
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<td>0.18</td>
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<tr>
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<td>2.8</td>
<td>0.44</td>
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</table>

Variables in italics denote statistically significant differences in means between criminals and non-criminals at least at the 10 percent significance level.
Table A3: Sample comparisons

Panel (a): Degree distribution of in-home criminals by friends’ nomination type

<table>
<thead>
<tr>
<th>Sample 1: criminals of the in-home sample</th>
<th>Sample 2: criminals of the in-home sample who nominate friends who are all in the in-home sample</th>
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</thead>
<tbody>
<tr>
<td>Kolmogorov Smirnov test: <strong>0.9935</strong></td>
<td>Whitney-Wolcox-Mann test: <strong>0.5767</strong></td>
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</tbody>
</table>

Panel (b): Degree distribution of in-home criminals by friends’ activity type

<table>
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<tr>
<th>Sample 1: criminals of the in-home sample</th>
<th>Sample 2: criminals of the in-home sample who nominate friends who are all criminals</th>
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</thead>
<tbody>
<tr>
<td>Kolmogorov Smirnov test: <strong>0.4199</strong></td>
<td>Whitney-Wolcox-Mann test: <strong>0.1498</strong></td>
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</table>

Notes: Degree is measured using out-degree. For each comparison, we even out the sample sizes of the two different samples by randomly removing nodes from the original (larger) one (see, e.g. Lehmann, 1998, Chapter 3). p-values of Kolmogorov Smirnov test and Whitney-Wolcox-Mann test in *italics*.
Table 1. 2SLS and GMM estimates of the crime model

<table>
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<tr>
<th></th>
<th>Finite-IV 2SLS</th>
<th>Many-IV 2SLS</th>
<th>Bias-Corrected 2SLS</th>
<th>Finite-IV GMM</th>
<th>Many-IV GMM</th>
<th>Bias-Corrected GMM</th>
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<td>Peer effects (φ)</td>
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<td>-0.0228</td>
<td>-0.0231</td>
<td>-0.0229</td>
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<td>(0.0243)</td>
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<td>(0.0243)</td>
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<tr>
<td>Two married parent family</td>
<td>-0.2633</td>
<td>-0.2665*</td>
<td>-0.2648*</td>
<td>-0.2596</td>
<td>-0.2619</td>
<td>-0.2605</td>
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<tr>
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<td>(0.1604)</td>
<td>(0.1604)</td>
<td>(0.1606)</td>
<td>(0.1604)</td>
<td>(0.1605)</td>
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<tr>
<td>Single parent family</td>
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<td>-0.2406</td>
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<td>(0.1620)</td>
<td>(0.1622)</td>
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<td>(0.1621)</td>
</tr>
</tbody>
</table>

Notes: Dependent variable: Index of delinquency. Different Estimators are summarized in Appendix D. The number of observations is 1,297 individuals over 150 networks. Estimated coefficients and Standard errors (in parentheses) are reported. *, **, *** denote statistical significance at the 10%, 5% and 1% level.
## Table 2. Robustness check: Endogenous crime participation

**Heckman selection model estimation**

### First step: selection equation

<table>
<thead>
<tr>
<th></th>
<th>Dep. Var.: Probability to become a delinquent</th>
<th>IV1: moral cost &amp; outside options</th>
</tr>
</thead>
<tbody>
<tr>
<td>Religion Practice</td>
<td>-0.0331*** (0.0132)</td>
<td>-0.0528** (0.0132)</td>
</tr>
<tr>
<td>Outside Options</td>
<td>-0.0891** (0.0436)</td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-3394.8303</td>
<td>-3396.6793</td>
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<tr>
<td>Pseudo R2</td>
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<td>0.0558</td>
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</table>

### Second step: outcome equation

<table>
<thead>
<tr>
<th></th>
<th>Dep. Var.: Index of delinquency</th>
<th>No exclusion restrictions</th>
<th>IV1: moral cost &amp; outside options</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peer effects (φ)</td>
<td>0.0412*** (0.0146)</td>
<td>0.0416*** (0.0148)</td>
<td>0.0416*** (0.0146)</td>
</tr>
<tr>
<td>Inverse Mills Ratio</td>
<td>2.2151* (1.2297)</td>
<td>1.4632 (0.9897)</td>
<td>2.1545** (0.9673)</td>
</tr>
<tr>
<td>Female</td>
<td>-0.3390*** (0.0732)</td>
<td>-0.3269*** (0.0671)</td>
<td>-0.3390*** (0.0719)</td>
</tr>
<tr>
<td>Student grade</td>
<td>0.0182 (0.0479)</td>
<td>0.0007 (0.0417)</td>
<td>0.0150 (0.0430)</td>
</tr>
<tr>
<td>Black or African American</td>
<td>0.0870 (0.1670)</td>
<td>0.0735 (0.1579)</td>
<td>0.0802 (0.1654)</td>
</tr>
<tr>
<td>Other races</td>
<td>0.0714 (0.1753)</td>
<td>0.0515 (0.1669)</td>
<td>0.0828 (0.1745)</td>
</tr>
<tr>
<td>Parental Education</td>
<td>-0.0033 (0.0412)</td>
<td>-0.0008 (0.0380)</td>
<td>-0.0030 (0.0407)</td>
</tr>
<tr>
<td>Mathematics score</td>
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<td>0.1111*** (0.0442)</td>
<td>0.1269*** (0.0468)</td>
</tr>
<tr>
<td>Self esteem</td>
<td>-0.0285 (0.0401)</td>
<td>-0.0185 (0.0364)</td>
<td>-0.0257 (0.0380)</td>
</tr>
<tr>
<td>Physical development</td>
<td>0.1401*** (0.0578)</td>
<td>0.1113*** (0.0469)</td>
<td>0.1350*** (0.0483)</td>
</tr>
<tr>
<td>Parental care</td>
<td>-0.2599* (0.1543)</td>
<td>-0.2307* (0.1355)</td>
<td>-0.2531* (0.1496)</td>
</tr>
<tr>
<td>School attachment</td>
<td>-0.0792* (0.0477)</td>
<td>-0.0678 (0.0420)</td>
<td>-0.0791* (0.0455)</td>
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<tr>
<td>Relationship with teachers</td>
<td>0.5014*** (0.1517)</td>
<td>0.4169*** (0.1191)</td>
<td>0.4926*** (0.1211)</td>
</tr>
<tr>
<td>Social inclusion</td>
<td>-0.1362*** (0.0563)</td>
<td>-0.1215*** (0.0499)</td>
<td>-0.1330*** (0.0540)</td>
</tr>
<tr>
<td>Residential building quality</td>
<td>0.1090** (0.0504)</td>
<td>0.0999** (0.0459)</td>
<td>0.1091** (0.0495)</td>
</tr>
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<td>Residential area urban</td>
<td>-0.0973 (0.1147)</td>
<td>-0.1275 (0.1031)</td>
<td>-0.0935 (0.1092)</td>
</tr>
<tr>
<td>Household size</td>
<td>-0.0149 (0.0286)</td>
<td>-0.0180 (0.0263)</td>
<td>-0.0162 (0.0281)</td>
</tr>
<tr>
<td>Two married parent family</td>
<td>-0.2718 (0.1867)</td>
<td>-0.2699 (0.1725)</td>
<td>-0.2732 (0.1855)</td>
</tr>
<tr>
<td>Single parent family</td>
<td>-0.2852 (0.1911)</td>
<td>-0.2721 (0.1758)</td>
<td>-0.2894 (0.1893)</td>
</tr>
</tbody>
</table>

### Notes:
- First stage probit estimation results and second stage finite-IV 2SLS estimation results are reported.
- **, ***, *** denote statistical significance at the 10%, 5% and 1% level.
### Table 3. Further robustness checks

#### Network misspecification issues

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<th>(2)</th>
<th>(3)</th>
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</thead>
<tbody>
<tr>
<td>Peer effects (φ)</td>
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<td>0.0655****</td>
<td>0.0698*</td>
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<td></td>
<td>(0.0215)</td>
<td>(0.0263)</td>
<td>(0.0371)</td>
</tr>
<tr>
<td>Female</td>
<td>-0.3642***</td>
<td>-0.4023***</td>
<td>0.0037</td>
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<tr>
<td></td>
<td>(0.0931)</td>
<td>(0.1065)</td>
<td>(0.0236)</td>
</tr>
<tr>
<td>Student grade</td>
<td>-0.0928**</td>
<td>-0.1134**</td>
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<tr>
<td></td>
<td>(0.0466)</td>
<td>(0.0536)</td>
<td>(0.091)</td>
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<tr>
<td>Black or African American</td>
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<td>0.1586</td>
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<tr>
<td></td>
<td>(0.2146)</td>
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<td>Other races</td>
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<td>-0.2028</td>
<td>0.0058</td>
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<tr>
<td></td>
<td>(0.2460)</td>
<td>(0.2746)</td>
<td>(0.0162)</td>
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<tr>
<td>Parental Education</td>
<td>0.0379</td>
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<tr>
<td></td>
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<td>(0.0588)</td>
<td>(0.0211)</td>
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<tr>
<td>Mathematics score</td>
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<td>(0.0203)</td>
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<td>0.0285</td>
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<tr>
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<td>(0.0456)</td>
<td>(0.0531)</td>
<td>(0.0183)</td>
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<tr>
<td>Physical development</td>
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<td>0.0315</td>
<td>-1.657**</td>
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<tr>
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<tr>
<td></td>
<td>(0.1697)</td>
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<tr>
<td>School attachment</td>
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<td>-0.0395</td>
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<tr>
<td></td>
<td>(0.0517)</td>
<td>(0.0604)</td>
<td>(0.0265)</td>
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<td>0.1595***</td>
<td>0.1390***</td>
<td>0.1390***</td>
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<tr>
<td></td>
<td>(0.0472)</td>
<td>(0.0536)</td>
<td>(0.0224)</td>
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<tr>
<td>Social inclusion</td>
<td>-0.1321**</td>
<td>-0.1583**</td>
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<td>(0.0633)</td>
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<td>(0.0275)</td>
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<tr>
<td>Residential building quality</td>
<td>0.1306**</td>
<td>0.1987***</td>
<td>0.0357</td>
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<td></td>
<td>(0.0636)</td>
<td>(0.0688)</td>
<td>(0.0573)</td>
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<tr>
<td>Residential Area Urban</td>
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<td>Two married parent family</td>
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<tr>
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<td>(0.2437)</td>
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</table>

Notes: Dependent variable: Index of delinquency. (1) Individuals who only nominate friends in the in-home survey. The number of observations is 648 individuals over 109 networks. (2) Individuals who only nominate friends who are criminals. The number of observations is 503 individuals over 98 networks. (3) Entire sample considering network of criminal and non-criminal friends. Finite-IV 2SLS estimated coefficients and standard errors (in parentheses) are reported. *, **, *** denote statistical significance at the 10%, 5% and 1% level.
Table 4. Who is the key player?

Significant differences

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<th>All Criminals</th>
<th>Key Player</th>
<th>t-test</th>
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<td></td>
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<td>St. dev</td>
<td>Mean</td>
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<td><strong>Individual characteristics</strong></td>
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<tr>
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<td>0.50</td>
<td>0.23</td>
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<tr>
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<td>1.41</td>
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<tr>
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<td>1.06</td>
<td>3.01</td>
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<td>1.00</td>
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<td>School attachment</td>
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<tr>
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<td>Two married parent families</td>
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<td>Parent occupation military or security</td>
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<td><strong>Friends’ characteristics</strong></td>
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<tr>
<td>Single parent families</td>
<td>0.14</td>
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<td>0.23</td>
</tr>
</tbody>
</table>

Number of obs.: 893  145

Notes: T-test for differences in means with unequal variances had been performed. P-values are reported.