The Strength of Weak Ties in Crime∗

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Abstract

The aim of this paper is to investigate whether weak ties play an important role in explaining criminal activities. We first develop a model where individuals learn about crime opportunities by interacting with active criminals. These interactions can take the form of either strong or weak ties. We find that, increasing the percentage of weak ties, induces more transitions from non-crime to crime and thus the crime rate in the economy increases. This is because, when the percentage of weak ties is high, delinquents and non-delinquents are in close contact with each other. We then test these predictions using the U.S. National Longitudinal Survey of Adolescent Health (AddHealth), which contains unique detailed informations on friendship relationships among delinquent teenagers. The theoretical predictions of our model are confirmed by the empirical analysis since we find that weak ties, as measured by friends of friends, have a positive impact on criminal activities.

Keywords: peer effects, network structure, delinquency.

JEL Classification: A14, K42

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1 Introduction

Granovetter (1973, 1974, 1983) argued that weak ties\footnote{Weak ties are acquaintances and strong ties are close friends.} are superior to strong ties for providing support in getting a job. Granovetter found that neighborhood based close networks were limited in getting information about possible jobs. In a close networks everyone knows each other, information is shared and so potential sources of information are quickly shaken down, the networks quickly becomes redundant in terms of access to new information. In contrast, Granovetter stresses the strength of weak ties involving a secondary ring of acquaintances who have contacts with networks outside ego’s network and therefore offer new sources of information on job opportunities. The network arrangements in play here involve only partially overlapping networks composed mainly of single-stranded ties.\footnote{Granovetter’s original paper presents evidence that weak ties are indeed important for finding a job. Of the job seekers finding jobs through friends and relative, 27.8% use weak ties, 16.7% use strong ties while the majority, 55.6%, use ties of moderate strength in between weak and strong. Other studies (summarized in Granovetter, 1983) found that between 13% and 76% of jobs were found by using information obtained through a weak tie. Montgomery (1994) proposed a model of weak ties in the labor market along these lines. Finally, a recent paper by Tassier (2006) shows that the breadth of social connections provided by weak ties has a significant effect on wages.}

In the present paper, we pursue this line of research by focussing on the role of weak ties in providing information about criminal activities. For that, we provide a theoretical analysis and test the predictions of the model using data on American teenagers.

While the importance of information about job opportunities seems clear in the labor market, one may wonder if the information about criminal offending opportunities is important for youth criminal behavior. The answer is yes and most of the evidence are coming from the criminology/sociology literature. In fact, both becoming a criminal and acquiring information about criminal opportunities when criminal are learned and transmitted through criminal friends. Indeed, 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, the most natural and efficient way to learn to become a criminal 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. This view of criminal networks and the role of peers in learning the technology of crime is not new, at least in the criminology literature. In his very influential theory of differential association, Sutherland (1947) locates the source of crime and delinquency in the intimate social networks of individuals. Emphasizing that criminal behavior is learned behavior, Sutherland (1947) argued that persons who are selectively or differentially exposed to delinquent associates are likely to acquire that trait as well. In particular, one of his main propositions states that when criminal behavior is learned, the learning includes (i) techniques of committing the crime, which are sometimes very complicated, sometimes very simple, (ii) the specific direction of
motives, drives, rationalization and attitudes. Furthermore, acquiring information about criminal opportunities is also through friends. For example, Weaver and Carroll (1985) studied the thought processes of seventeen expert and seventeen novice shoplifters during consideration of actual crime opportunities. One aspect that was crucial in differentiating experts from novices was the transmission of information about crime opportunities. Experts were much more efficient and less likely to be caught than novices because of their connections with other experienced criminals who could transmit valuable information about criminal opportunities. In a gang also the transmission of criminal information is crucial. Using data from the Rochester Youth Development study, which followed 1,000 adolescents through their early adult years, Thornberry et al. (1993) find that once individuals become members of a gang, their rates of delinquency increase substantially compared to their behavior before entering the gang. In other words, networks of criminals or gangs amplify delinquent behaviors. One aspect that is crucial in a gang is the transmission of information about job opportunities, which reduces the possibility to be caught. Gang membership is thus viewed as a major cause of deviant behavior. This is also what is found by Warr (2002) and Thornberry et al. (2003).

In economics, the influence of peers/friends on criminal behaviors has also been studied. Case and Katz (1991), using data from the 1989 NBER survey of youths living in low-income Boston neighborhoods, find that a 10 percent increase in the neighborhood juvenile crime rate increases the individual probability to become a delinquent by 2.3 percent. Ludwig et al. (2001) and Kling et al. (2005) explore this last result by using data from the Moving to Opportunity (MTO) experiment that relocates families from high- to low-poverty neighborhoods. They find that this policy reduces juvenile arrests for violent offences by 30 to 50 percent of the arrest rate for control groups. This also suggests very strong social interactions in crime behaviors. More recently, Calvó-Armengol et al. (2005) test whether the position and the centrality of each delinquent in a network of teenager friends has an impact on crime effort. They show that, after controlling for observable individual characteristics and unobservable network specific factors, the individual’s position in a network is a key determinant of his/her level of criminal activity.

From a theoretical point of view, there is a growing literature on the social aspects of crime. In Sah (1991), the social setting affects the individual perception of the costs of crime, and is thus conducive to a higher or a lower sense of impunity. In Glaeser et al. (1996), criminal interconnections act as a social multiplier on aggregate crime. Calvó-Armengol and Zenou (2004) and Ballester et al. (2004, 2006) develop a more general model by studying the effect of the structure of the social network on crime. They show that the location in the social network is crucial to understand crime

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3 Two more recent papers by Chen and Shapiro (2003) and Bayer et al. (2003) find also strong peer effects in crime by investigating the influence individuals serving time in the same facility have on the subsequent criminal behavior of offenders. The former shows that worsening prison conditions significantly increases post-release crime. The latter provides strong evidence that, for many types of crimes, learning is significantly enhanced by access to peers with experience with that crime.
and that not only direct friends but also friends of friends of friends, etc. have an impact of criminal activities and the decision to become a criminal.\(^4\)

In the present paper, we consider a model in which individuals belong to mutually exclusive two-person groups, referred to as dyads. Dyad members do not change over time so that two individuals belonging to the same dyad hold a strong tie with each other. However, each dyad partner can meet other individuals outside the dyad partnership, referred to as weak ties or random encounters. By definition, weak ties are transitory and only last for one period.

Individuals learn about crime opportunities by interacting with active criminals. These interactions can take the form of either strong or weak ties. The process through which individuals learn about crime behavior and opportunities results from a combination of a socialization process that takes place inside the family and best friends (in the case of strong ties) and a socialization process outside the family and best friends (in the case of weak ties). Bisin and Verdier (2000) refer to the former as vertical socialization and to the latter as oblique socialization. Both currently active criminals and potential criminals exert an influence over one another to commit offences by meeting each other.

We analyze the flows of dyads between states and characterize the steady-state equilibria of this economy. There is one equilibrium where no crime is committed and another one where crime exists in equilibrium. By focussing on the latter, we analyze the impact of weak ties on each dyad and on the crime level in the economy. We find that, increasing the percentage of weak ties, induces more transitions from non-crime to crime and thus the crime rate in the economy increases. This is because, when the percentage of weak ties is high, delinquents and non-delinquents are in close contact with each other.

We test these predictions using the U.S. National Longitudinal Survey of Adolescent Health (AddHealth), which contains unique detailed information on friendship relationships among delinquent teenagers. This dataset provides information on the best friends of each adolescent (i.e. strong ties) and we can thus define weak ties as friends of best friends, and friends of friends of best friends, etc. The interesting aspect of this definition is that it avoids some endogeneity problem because if individuals choose their best friends they do not obviously choose the friends of their best friends, and even less the friends of friends of their best friends, etc. The theoretical predictions of our model seem to be confirmed by the empirical analysis since weak ties have a positive impact on criminal activities.

\(^4\)Linking social interactions with crime has also been done in dynamic general equilibrium models (Imrohoroglu et al., 2000, and Lochner 2004) and in search-theoretic frameworks (Burdett et al., 2003, 2004, and Huang et al., 2004). Other related contributions on the social aspects of crime include Silverman (2004), Verdier and Zenou (2004), Calvó-Armengol et al. (2007), Patacchini and Zenou (2004).
2 Theoretical analysis

2.1 The model

Consider a population of individuals of size one. Individuals are either non-criminal or involved in criminal activities. Consistent with our dataset, we focus on petty crimes committed by adolescents.

**Dyads** We assume that individuals belong to mutually exclusive two-person groups, referred to as dyads. We say that two individuals belonging to the same dyad hold a strong tie with each other. We assume that dyad members do not change over time. A strong tie is created once and for ever, and can never be broken. We can thus think of strong ties as links between members of the same family, or between very close friends.

Individuals can be in either of two different states: criminal or not criminal. Dyads, which consist of paired individuals, can thus be in three different states, which are the following:

(i) both members are criminals – we denote by \( d_2 \) the number of such dyads;
(ii) one member is criminal and the other is not (\( d_1 \));
(iii) both members are not criminal (\( d_0 \)).

**Aggregate state** Denoting by \( c(t) \) and \( u(t) \) respectively the criminal rate and the non-criminal rate at time \( t \), where \( c(t), u(t) \in [0, 1] \), we have:

\[
\begin{align*}
    c(t) &= 2d_2(t) + d_1(t) \\
    u(t) &= 2d_0(t) + d_1(t)
\end{align*}
\]

The population normalization condition can then be written as

\[ c(t) + u(t) = 1 \]

or, alternatively,

\[ d_2(t) + d_1(t) + d_0(t) = \frac{1}{2} \]

**Social interactions** Time is continuous and individuals live for ever.

We assume that individuals randomly meet by pairs repeatedly through time. Matching can take place between dyad partners or not. At each period, any given individual is matched with his dyad partner with probability \( 1 - \omega \), while he is matched randomly to any other individual in the population with complementary probability \( \omega \).

We refer to matchings inside the dyad partnership as strong ties \((1 - \omega)\) and to matchings outside the dyad partnership as weak ties or random encounters \((\omega)\). By definition, weak ties are

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\(^5\)The inner ordering of dyad members does not matter.
transitory and only last for one period. Within each matched pair, information is exchanged, as explained below.

**Information transmission** Individuals are aware of some criminal activity at exogenous rate $\lambda$. Delinquents pass this information on to their current matched partner, be it a strong tie or a weak tie. Information about crime is thus essentially obtained through friends and relatives (i.e. strong and weak ties). This information transmission protocol defines a Markov process. The state variable is the relative size of each type of dyad. Transitions depend on the crime market, and on the nature of social interactions as captured by $\omega$.

We denote by $p$ the rate at which criminals are caught. Here, when a criminal is caught, he spends some time in prison and then gets out. Because we are dealing with petty crime committed by adolescents, we assume that the time spent in prison is short enough so that the strong tie’s status does not change meanwhile.

**Flows of dyads between states** It is readily checked that the net flow of dyads from each state between $t$ and $t + dt$ is given by:

\[
\begin{align*}
\dot{d}_2(t) &= h(c(t))d_1(t) - 2pd_2(t) \\
\dot{d}_1(t) &= 2g(c(t))d_0(t) - [p + h(c(t))]d_1(t) + 2pd_2(t) \\
\dot{d}_0(t) &= pd_1(t) - 2g(c(t))d_0(t)
\end{align*}
\]

where $h(c(t)) = (1 - \omega + \omega c(t))\lambda$ is the probability to hear from a crime opportunity either by a weak or a strong tie ($\lambda$ is the rate at which ‘potential’ criminals hear from a crime opportunity) and $g(c(t)) \equiv \omega c(t)\lambda$ is the probability to hear from a crime opportunity only by weak ties.

These dynamic equations reflect the flows across dyads. Graphically,

![Figure 1. Flows in the crime market](image)

For instance, in the first equation, the variation of dyads composed of two criminals ($\dot{d}_2(t)$) is equal to the number of $d_1$-dyads in which the non-criminal individual has found a crime opportunity (through either his strong tie with probability $(1 - \omega)\lambda$ or his weak tie with probability $\omega c(t)\lambda$)
minus the number of $d_2$–dyads in which one the two criminals has been caught. All the other equations have a similar interpretation. Observe that we assume here that whenever someone has a crime opportunity, he/she takes it.

Taking into account (3), the system (4) reduces to a two-dimensional dynamic system in $d_2(t)$ and $d_1(t)$ given by:

\[
\begin{align*}
\dot{d}_2(t) &= h(c(t))d_1(t) - 2pd_2(t) \\
\dot{d}_1(t) &= 2g(c(t))(1/2 - d_2(t) - d_1(t)) - [p + h(c(t))]d_1(t) + 2pd_2(t)
\end{align*}
\]

where, using (1):

\[c(t) = 2d_2(t) + d_1(t)\]

### 2.2 Steady-state equilibrium analysis

At a steady-state $(d_2^*, d_1^*, d_0^*)$, each of the net flow in (4) is equal to zero. Setting these net flows equal to zero leads to the following relationships:

\[
\begin{align*}
d_2^* &= \frac{(1 - \omega + \omega c^*)\lambda}{2p} d_1^* \\
d_1^* &= \frac{2\omega c^* \lambda}{p} d_0^* \\
d_0^* &= \frac{1}{2} - d_2^* - d_1^* \\
c^* &= 2d_2^* + d_1^*
\end{align*}
\]

where

\[d_0^* = \frac{1}{2} - d_2^* - d_1^*\]  
\[c^* = 2d_2^* + d_1^*\]  

**Definition 1** A steady-state labor market equilibrium is a four-tuple $(d_2^*, d_1^*, d_0^*, c^*)$ such that equations (5), (6), (7) and (8) are satisfied.

Define $Z = (1 - \omega) / \omega$, $B = p/ (\lambda \omega)$. We have the following result.

**Proposition 1**

(i) There always exists a steady-state equilibrium $U$ where all individuals are non criminals and only $d_0$–dyads exist, that is $d_2^* = d_1^* = c^* = 0$, $d_0^* = 1/2$ and $c^* = 0$.

(ii) If

\[p < \lambda[\omega + \sqrt{\omega(4 - 3\omega)}]/2\]

there exists a steady-state equilibrium $C$ where $0 < c^* < 1$ is implicitly defined by

\[c^* = \frac{B^2}{2d_0^*} - B - Z > 0,\]
and $0 < d_0^* < 1/2$ is the unique solution of the following equation:

$$-\frac{Z}{B}d_0^* - \frac{(1 + Z)}{2}d_0^* + \left(\frac{B}{2}\right)^2 = 0$$

(11)

Also, the other dyads are given by:

$$d_1^* = \frac{2c^*}{B}d_0^*$$

(12)

$$d_2^* = \frac{(Z + c^*)c^*}{B^2}d_0^*$$

(13)

Proof. See Appendix 1.

If condition (9) holds, then an interior equilibrium always exists. This condition says that the probability $p$ to be caught should not be too high compared to $\lambda$, the rate at which individuals are aware of some criminal activity. This is very reasonable in our framework since we focus on teenagers committing petty crime (see the description of our data in the next section).

2.3 Comparative statics analysis

We are interested on the impact on weak ties $\omega$ on crime. For that, we focus on the interior equilibrium $C$, defined above, where $0 < c^* < 1$. We have the following result:

**Proposition 2** Consider the steady-state equilibrium $C$ and assume that $2p/(\omega \lambda) < d_0$. Then, increasing the percentage of weak ties $\omega$ decreases the number of $d_0$–dyads but increases the crime rate $c^*$ in the economy, i.e.

$$\frac{\partial d_0^*}{\partial \omega} < 0, \quad \frac{\partial c^*}{\partial \omega} > 0$$

The effects of $\omega$ on $d_1^*$ and on $d_2^*$ are however ambiguous.

Proof. See Appendix 1.

Here, individuals belong to mutually exclusive groups, the dyads, and weak tie interactions spread information across dyads. The parameter $\omega$ measures the proportion of social interaction that occurs outside the dyad, the inter-dyad interactions. When $\omega$ is high, the social cohesion among criminals is low, and delinquents and non-delinquents are in close contact with each other. In this context, increasing $\omega$ induces more transitions from non-crime to crime and thus $c^*$, the crime rate in the economy increases. Even though $c^*$ increases, the effect of $\omega$ on $d_2^*$ and $d_1^*$ is ambiguous. Indeed, from Figure 1, individuals leave dyad $d_1$ and enters dyad $d_2$ at rate $(1 - \omega + \omega c)\lambda$. Now since

$$\frac{\partial [(1 - \omega + \omega c)\lambda]}{\partial \omega} = (-1 + c + \omega \frac{\partial c}{\partial \omega})\lambda$$

is ambiguous (since $-1 + c < 0$), the effects mentioned above are also ambiguous. Now consider the effect of $\omega$ on $d_0^*$. This is clearly negative. Indeed, from Figure 1, one can see that individuals
leave dyad $d_0$ at rate $2\omega c \lambda$. Since

$$\frac{\partial (2\omega c \lambda)}{\partial \omega} = 2\lambda \left( c + \omega \frac{\partial c}{\partial \omega} \right) > 0$$

then, when $\omega$ increases, there are fewer $d_0$–dyads.

To summarize, the effect of weak ties $\omega$ on crime $c^*$ is positive because when $\omega$ increases, the transition from non-crime to crime increases since $\frac{\partial d^*}{\partial \omega} < 0$, even though we do not know if criminals are more likely to be part of a $d_1$ or $d_2$–dyad.

3 Empirical Analysis

We now perform an empirical investigation to verify whether this model is validated by the real world evidence. In summary, the model predicts that, when the percentage of weak ties in the economy increases, then the overall crime rate in the economy increases and the number of $d_0$ dyadic structures (i.e. noncriminals whose best friends are noncriminals) are reduced. For the number of criminals whose best friends are criminals ($d_2$–dyad) and the number of criminals whose best friends are non criminals ($d_1$–dyads), the theoretical impact is ambiguous.

The empirical strategy is as follows.

Using a sample of criminal and non-criminal individuals embedded in friendship networks, we first estimate the impact of percentage of weak ties both on the level of criminal activity and on the individuals’ probability of committing crime. Subsequently, we select different sub-samples in order to resemble the different dyadic structures between each individual and her/his best friends (strong ties) and we investigate whether a change in the percentage of weak ties produces an effect in line with the predicted ones.

3.1 Data and definition of variables

Our data source is the National Longitudinal Study of Adolescent Health (Add Health), which is a study of a nationally representative sample of more than 90,000 adolescents in grades 7-12 in the United States in 1994-95. The AddHealth website describes surveys and data in details.6 Besides information on family background, friends, school quality and area of residence, the AddHealth contains also sensitive data on sexual behavior (contraception, pregnancy, AIDS risk perception), tobacco, alcohol, drugs and crime (ranging from light offenses to serious property and violent crime) of a subset of adolescents (roughly 20,000).

We measure the individual level of criminal activity by adopting the standard approach in the sociological literature, which uses an index of delinquency involvement based on self-reported adolescents’ responses to a set of questions describing participation in a series of criminal activities.

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6http://www.cpc.unc.edu/projects/addhealth
The AddHealth contains information on 15 delinquency items. The survey asks students how often they participate in each of the different 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). On the basis of these scores, a summated index is calculated for each respondent. The mean is 1.03, with considerable variation around this value (the standard deviation is equal to 1.22). The Crombach $\alpha$ measure is then used to assess the quality of the derived variable. In our case, we obtain an $\alpha$ equal to 0.76 ($0 \leq \alpha \leq 1$) indicating that the different items incorporated in the index have considerable internal consistency.

The key variable in the theoretical analysis is friendship tightness or weak ties $\omega$. Finding its empirical counterpart is quite a difficult task. Our analysis is made possible by the unique detailed information on friendship relationships contained in the AddHealth data. Pupils were asked to identify their best friends from a school roster (up to five males and five females), and this information allows to reconstruct the whole geometric structure of the friendship networks. Our proxy of weak ties $\omega$ is calculated as follows. For each individual, the percentage of all friends of best friends over all the individuals in the network will be the counterpart of $\omega$. Let us be more precise about this measure.

Let $N_\kappa = \{1, \ldots, n_\kappa\}$ be the finite set of individuals (here teenagers) in network $g_\kappa$. We keep track of social connections by a network $g_\kappa$, where $g_{ij,\kappa} = 1$ if $i$ and $j$ are best friends, and $g_{ij,\kappa} = 0$, otherwise. Given that friendship is a reciprocal relationship, we set $g_{ij,\kappa} = g_{ji,\kappa}$. We also set $g_{ii,\kappa} = 0$. Assume that there are $K$ network components in the economy, i.e., $\kappa = 1, \ldots, K$. Network components are maximally connected networks, that satisfy the two following conditions. First, two individuals in a network component $g_\kappa$ are either directly linked, or are indirectly linked through a sequence of agents in $g_\kappa$. Second, two agents in different network components $g_\kappa$ and $g_\kappa'$ cannot be connected through any such sequence.

Formally, we define by $\Omega^S_{i,\kappa}$ the number of strong ties of each agent $i$ in network $g_\kappa$, the number

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7Namely, paint graffiti or signs on someone else’s property or in a public place; deliberately damage property that didn’t belong to you; lie to your parents or guardians about where you had been or whom you were with; take something from a store without paying for it; get into a serious physical fight; hurt someone badly enough to need bandages or care from a doctor or nurse; run away from home; drive a car without its owner’s permission; steal something worth more than $50; go into a house or building to steal something; use or threaten to use a weapon to get something from someone; sell marijuana or other drugs; steal something worth less than $50; take part in a fight where a group of your friends was against another group; act loud, rowdy, or unruly in a public place.

8Respondents listened to pre-recorded questions through earphones and then they 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.

9Thus, in a network a link exists between two friends if at least one of the two individuals has identified the other as his/her best friend. Note that, when an individual $i$ identifies a best friend $j$ who does not belong to the same school, the database does not include $j$ in the network of $i$; it provides no information about $j$. Fortunately, in the majority of cases, best friends tend to be in the same school and thus are systematically included in the network.
of best friends of \( i \) in \( g_\kappa \), that is:

\[
\Omega_{i,\kappa}^S(g_\kappa) = \sum_{j=1}^{N} g_{ij,\kappa}
\]

Accordingly, the number of weak ties of each agent \( i \), \( \Omega_{i,\kappa}^W \), will be all individuals who are not his/her best friends, that is:

\[
\Omega_{i,\kappa}^W(g_\kappa) = n_\kappa - \Omega_{i,\kappa}^S(g_\kappa) = n_\kappa - \sum_{j=1}^{N} g_{ij,\kappa}
\]

Observe that, by definition of a network component, two individuals in a network component \( g_\kappa \) are either directly linked (strong ties), or are indirectly linked (weak ties) through a sequence of agents in \( g_\kappa \). This is why the number of weak ties is \( n_\kappa \) minus the number of strong ties.

For each individual, we normalize these values by dividing for the total number of direct and indirect friends, so that they sum up to 1 for each agent. Thus the percentage of strong and weak ties each individual \( i \) has in network \( g_\kappa \) is respectively given by:

\[
1 - \omega_{i,\kappa}(g_\kappa) = \frac{\Omega_{i,\kappa}^S(g_\kappa)}{n_\kappa} = \frac{\sum_{j=1}^{N} g_{ij,\kappa}}{n_\kappa}
\]

\[
\omega_{i,\kappa}(g_\kappa) = \frac{\Omega_{i,\kappa}^W(g_\kappa)}{n_\kappa} = \frac{n_\kappa - \sum_{j=1}^{N} g_{ij,\kappa}}{n_\kappa}
\]

Observe that there is a strong exogenous component in this last measure since the friends of friends ... of best friends of agent \( i \) can be reasonably considered as given for each individual \( i \).

By matching the identification numbers of the friendship nominations to respondents’ identification numbers, it is possible to obtain information on the characteristics of nominated friends.\(^{10}\) The control variables used in the empirical analysis are described in Appendix 2. Table 1 provides descriptive statistics on the adolescents in our sample. Excluding the individuals with missing or inadequate information, we obtain a final sample of 9,322 individuals. Table 1 reveals that, for instance, the average student is in grade 9, has spent more than 3 years in the school, is fairly motivated in education, with a good relationship with teachers, whose parents have a level of education higher than high school degree and lives in a fairly well kept building. School and teacher quality are about average and the 34 percent of students attends a private school. The variables indicating the interaction with friends and parents show a high involvement in friends’ relations and a high level of parental care. Almost 80 percent of the adolescents live in households with two parents, but only in the 42 percent of the cases parents are married. Finally, for our variable of interest \( \omega_{i,\kappa}(g_\kappa) \), on can see that, on average, an individual has 66 percent of his/her friends that are weak ties.

\(^{10}\)We use this proxy of weak ties, which simply counts the number of indirect links to provide a test of our model. Our analysis has also been performed selecting in our measure only weak tie friends who are criminal. The results are qualitatively unchanged, although the estimated effects are larger in magnitude, as it is expected.
3.2 Econometric issues and empirical model

We have already highlighted in Section 3.1 that our measure of weak ties may be considered as exogenous for each agent \( i \), given the (indirect) way this measure is constructed. However, a couple of other empirical issues remain to be addressed. Firstly, we need to rule out the possibility that our measure of weak ties, which derives from the fact that some individuals hang out with friends more occasionally than others, is simply picking up social isolation or other unobserved individual characteristics. In other words, our aim is to exclude the possibility that the relationship between weak ties and crime effort would be the result of correlations between crime activity and factors related to specific groups of people, e.g. socially isolated individuals, single parent pupils, children of low educated parents, individuals of a particular race or individuals living in certain environments, e.g. poor quality neighborhood, school with religious affiliation, etc.

Table 2 reports the various correlations, using as measures of social integration an indicator of self-esteem, the level of school attachment, social exclusion and the fraction of best friends that also report the reference individual as a best friend (denoted as symmetric friendship ties) (see Appendix 2 for precise definitions of variables). They show extremely low values for all the groups considered, indicating no evident sign that weak ties might capture some (unobserved) characteristics of particular groups of individuals possibly not accounted by our list of observable in the regression model.

The second issue to be addressed is the possibility that peers may be exposed to similar environmental influences, which are not observable. In this respect, because the AddHealth survey interviews all children within a school, we estimate our model conditional on school fixed effects. The inclusion of school dummies captures the effects of (observable and unobservable) school-specific factors, so that only the variation in the percentage of weak ties friends (across students in the same school) would be exploited. Observe that this is particularly important in our analysis because the broadness of individual social networks (and thus possibly our measure of weak ties) might be correlated with school size. One might argue, however, that school fixed effects do not account for a possible heterogeneity in school environmental factors within schools, i.e. within each given network. Clearly agents sort into networks and there might be some unobserved network

\[\text{Insert Table 1 here}\]

\[\text{Insert Table 2 here}\]

11Observe that we do not encounter here the identification problems that are common in examining the effect of social interactions. Indeed, one should not expect the characteristics of the members of one group (i.e. the so-called contextual effect) to directly affect the outcome of members of another group to which they are not directly tied to.
characteristics driving network members’ behavior. Assuming additively separable group heterogeneity, a within group specification is able to control for these issues. In other words, we introduce a network-specific component in the error term, and adopt a traditional (pseudo) panel data fixed effect approach, namely, we subtract from the individual-level variables the network component average.

Specifically, we estimate the following model, where our measure of weak ties, \( \omega_{i,\kappa} \equiv \omega_{i,\kappa}(g_\kappa) \), has been separated out from the other explanatory variables for ease of exposition:

\[
c_{i,\kappa} = \beta \omega_{i,\kappa} + \sum_{l=1}^{L} \gamma_l x_{i,\kappa}^l + \eta_\kappa + \varepsilon_{i,\kappa}, \quad \text{for } i = 1, \ldots, N_\kappa; \kappa = 1, \ldots, K
\] (16)

Our dependent variable, \( c_{i,\kappa} \), is either the level of criminal activity or the probability of committing crime for individual \( i \) in network \( g_\kappa \). \( x_{i,\kappa}^l \) denotes a set of \( L \) control variables for individual \( i \) in network \( g_\kappa \) (including a constant term) and the error term consists of a network specific component (constant over individuals in the same network), which might be correlated with the regressors, \( \eta_\kappa \), and a white noise component, \( \varepsilon_{i,\kappa} \).

A (pseudo) panel data fixed effect estimator is adopted. When the probability of committing crime is analyzed (non linear dependent variable), we employ a probit estimator, whereas when the level of criminal activity is considered (linear dependent variable), we use a OLS estimator. The estimated value \( \hat{\beta} \) of \( \beta \) measures the empirical impact of percentage of weak ties on criminal outcomes.

### 3.3 Estimation results

The estimation of model (16) has been performed using different model specifications where different sets of controls have been added (see Appendix 2). We start by including standard individuals’ characteristics and behavioral factors (i.e., socio-demographic factors, family background, motivation in education and a proxy for individual ability, namely mathematics score). Then, we gradually introduce protective factors (i.e., relationship with teachers, social exclusion, school attachment, parental care), residential neighborhood characteristics and school characteristics. In addition, the richness of the information provided by the AddHealth questionnaire on adolescents’ behavior allow us to find proxies for typically unobserved individual characteristics that may contaminate our target coefficients. In particular, we control for differences in leadership propensity across teenagers by adding indicators of self-esteem and level of physical development compared to the peers.\(^{12}\)

Table 3 reports the estimation results of the final specification of model (16), which includes a complete set of controls for our two different dependent variables, \( c_{i,\kappa} \). The estimated effects of

\(^{12}\) The introduction of student-grade or student-year of attendance in the school dummies does not change qualitatively the results.
the control variables are qualitatively the same across all model specifications and in line with the expectations.\textsuperscript{13}  

\[\text{Insert Table 3 here}\]

The table reveals that, irrespective of the specification of the dependent variable, the estimated effect of weak ties in shaping criminal behavior (first row in Table 3) is positive and highly statistically significant. This evidence indicates that, after accounting for the effects of an (unusually) extensive set of observable individual characteristics and unobservable network specific factors, the more weak ties an adolescent has, the higher the probability of becoming criminal and his/her delinquency activity. This is consistent with Proposition 2.

However, regarding the magnitude of the effects, we find that the impact of weak ties is particularly influential in raising the probability of becoming a criminal, whereas it is only minor in increasing the level of criminal activity. Specifically, a marginal increase in the percentage of weak ties raises the average probability of committing crime by roughly 20 percent. When we consider the level of criminal activity as dependent variable, having a high percentage of weak tie friends raises the individual delinquency by 0.13, which correspond to less than 0.07 of a standard deviation.

\textbf{Estimation results - different types of crime-}

The richness of the information provided by the AddHealth data on juvenile crime enables us to perform our analysis on different types of criminal activities separately. We split our sample of teenagers according to the seriousness of their crime (with increasing costs of committing crime). The first group contains those declaring (i) to have painted graffiti or signed on someone else’s property or in a public place; (ii) lie to your parents or guardians about where you had been or whom you were with; (iii) run away from home; (iv) act loud, rowdy, or unruly in a public place (\textit{type-1 crimes}). The second group consists of those declaring (i) get into a serious physical fight; (ii) hurt someone badly enough to need bandages or care from a doctor or nurse; (iii) drive a car without its owner’s permission; (iv) steal something worth less than $50 (\textit{type-2 crimes}). Finally, the third group includes those who (i) take something from a store without paying for it; (ii) steal something worth more than $50; (iii) go into a house or building to steal something; (iv) use or threaten to use a weapon to get something from someone; (v) sell marijuana or other drugs (\textit{type-3 crimes}). Less than 20 percent of the teenagers in our sample confess to have committed the more serious offences. We have 2,769, 4,798 and 1,755 individuals in the three groups respectively.\textsuperscript{14} The estimation results of model (16) run separately on those groups are contained in Table 4.

\[\text{Insert Table 4 here}\]

\textsuperscript{13}The complete list of estimation results for all the variables across the different model specification are available upon request.

\textsuperscript{14}Adolescents are selected in a more serious type of crime group if they have committed at least one of the offences considered in each type of crime.
The estimated impact of the percentage of weak ties is positive and statistically significant for all types of crime, regardless of the dependent variable used. However, it varies largely in magnitude across groups. The reported marginal effects decrease from roughly 50 percent to less than 9 percent moving from light offences (type 1) to more serious crime (type 3). Specifically, a marginal increase in the percentage of weak ties raises the average probability of committing crime by roughly 50 percent for petty crimes (type-1 crimes) and by less than 9 percent for more serious crimes (type-3 crimes). When we consider the level of criminal activity as dependent variable, in terms of standard deviations the corresponding range of the effect is between 0.26 and 0.02. Not surprisingly, the influence of weak ties friends is stronger for petty crime than for more serious crime. This is consistent with the results of Glaeser et al. (1996), who show that social interactions prevail more in petty crimes.

**Estimation results - split samples**

In order to investigate in more details the results of our theoretical model, we would like now to see how weak ties affect the different dyads. In other words, does the estimated relationship between individual percentage of criminal weak ties and individual criminal activity hold true once the structure of the individual’s percentage of criminal strong ties has been controlled for? To answer this question, we evaluate the impact of weak ties on the probability of becoming a criminal splitting the sample between individuals (criminals and noncriminal) who have most (i.e., more than 60 percent) of their best friends (strong ties) who are criminals (sub-sample (i)) and those having most (more than 60%) of their best friends who are noncriminal (sub-sample (ii)). The two sub-samples contain 3,304 and 3,785 individuals respectively.\(^{15}\)

Finally, for completeness, we also investigate whether the evidence of an increase in criminal activity following an increase in the percentage of weak ties holds true when only the sub-sample of criminals having most of their best friends criminals (sub-sample (iii), which corresponds to \(d_2\)–dyads in the theoretical model) is considered. This sub-sample contains 2,423 individuals.

The estimation results are contained in Table 5. As before, network-specific unobserved effects are considered in all specifications. The first two columns report the results obtained employing a (pseudo) panel data fixed effects probit estimator on sub-samples (i) and (ii) respectively, whereas the third column contains the results obtained employing a (pseudo) panel data fixed effects OLS estimator on sub-sample (iii).

[Insert Table 5 here]

The impact of weak ties remains positive and highly statistically significant in all sub-samples, regardless of the proxy used. In particular, the probability to commit crime seems to increase for those having noncriminal best friends. This evidence is in line with the theoretical model, which \(^{15}\)The remaining 2,233 individuals of the original sample have between 40% and 60% of criminal (or non criminal) best friends. Other thresholds, i.e. more than 70 and 80 percent, have also been used. The results remain qualitatively unchanged. We thus present the results obtained using the less stringent value to preserve the sample sizes of our target samples.
predicts that when the percentage of criminal weak ties increases the number of $d_0$ dyadic structures (i.e., noncriminal whose best friends are noncriminal) is reduced (see Proposition 2).

Looking at the magnitude of the estimated effect across sub-samples (i) and (ii), quite interestingly it appears that being inclined towards weak ties has an extremely relevant impact in raising the probability of committing crime for those having noncriminal strong ties (sub-sample (ii), second column), whereas the effect is negligible for those having criminal best friends (sub-sample (i), first column). Specifically, a marginal increase in the percentage of weak ties raises the average probability of committing crime by roughly 30 percent with sub-sample (ii). These effects are only 9 percent when the analysis is run on sub-sample (i). Consistent with Proposition 2, these results mean that having more weak ties tends to decrease the number of $d_0$ dyads since the probability to become a criminal increases.

When we restrict the analysis to sub-sample (iii) and evaluate the impact of weak ties on the level of criminal activity (last column), we find that the responsiveness of our dependent variable is considerable. Specifically, being inclined towards weak ties raises the individual delinquency by 0.49, which corresponds to roughly one fourth of a standard deviation of the delinquency index.

3.4 Robustness checks

We perform two different robustness checks, which consist in using two alternative measures of weak ties.

Our first exercise is motivated by the fact that our measure of weak ties assigns the same weight to each weak tie friend, as it simply counts the number of all indirect links in a network. One may argue that in fact the amount of information possibly conveyed to each agent by friends of best friends is different from that given by friends of friends of....friends of friends, because the chance to meet these latter friends are clearly lower. We then repeat our empirical analysis using another proxy for weak ties. Instead of taking all possible friends of friends of individual $i$, we only focus of friends of length two, that is only the best friends of the best friends of individual $i$. To be more precise, define a simple path of length 2 from $i$ to $j$ in $g_\kappa$ as a sequence $(i_0, i_1, i_2)$ of individuals such that $i_0 = i$, $i_1 = k$, $i_2 = j$, with $i_0 \neq i_1 \neq i_2$, and $g_{i_0i_1,\kappa} = 1$, $g_{i_1i_2,\kappa} = 1$, that is, individuals $i_0$ and $i_1$ as well as $i_1$ and $i_2$ are directly linked in $g_\kappa$. We denote such a simple path of length 2 between $i$ and $j$ as $g_{ij,\kappa}^{[2]}$. Then, the percentage of weak ties is now defined as:

$$\omega_{i,\kappa}^{[2]}(g_\kappa) = \frac{\sum_{j=1}^{N} g_{ij,\kappa}^{[2]}}{n_\kappa}$$

Of course now $1 - \omega_{i,\kappa}^{[2]}(g_\kappa)$ is not anymore the percentage of strong ties.

Panels (a) in Tables 6 and 7 display the results for the whole sample and the split samples, respectively, corresponding to Tables 3 and 5 for $\omega_{i,\kappa}(g_\kappa)$. It is easy to see that the use of $\omega_{i,\kappa}^{[2]}(g_\kappa)$ do not change qualitatively the results: weak ties have still a positive and significant effect on
crime. In terms of magnitude, if we consider the level of criminal activity as dependent variable for
the whole sample (Panel (a) in Table 7), then having a high percentage of weak tie friends raises
the individual delinquency by 0.55, which correspond to 0.13 of a standard deviation. Compared
to \( \omega_{i,\kappa}(g_{\kappa}) \), the effect is almost double. Concerning the split samples (Panel (a), Table 8), the
effects are roughly similar. Consider for example sub-sample (iii), then the impact is roughly 0.30
in terms of a standard deviation whereas we had roughly 0.25 with \( \omega_{i,\kappa}(g_{\kappa}) \).

Our second exercise, instead, consists in using a proxy for weak ties that excludes the friends
of length two. The concern addressed here is the possibility that individuals may anticipate the
anti-social or pro-social behavior of the close friends of their best friends when selecting their best
friends. However, it is reasonable to assume that this is less likely to be true the higher is the
length of the path between individual \( i \) and a given indirect friend. Therefore we exclude from our
measure of weak ties the best friends of the best friends of individual \( i \). Specifically, the percentage
of weak ties is now defined as:

\[
\omega_{i,\kappa}^{[\geq 3]}(g_{\kappa}) = \frac{n_{\kappa} - \sum_{j=1}^{N} g_{ij,\kappa} - \sum_{j=1}^{N} g_{i[j]^2}}{n_{\kappa}}
\]

The estimation results are contained in panels (b) in Tables 6 and 7. The evidence here is both
qualitatively and quantitatively almost unchanged with respect to that of Tables 3 and 5. This
indicates that, once our set of individual, residential neighborhood and school characteristics is
taken into account, our measure of weak ties (\( \omega_{i,\kappa}(g_{\kappa}) \)) can be reasonably taken as exogenous.

4 Conclusion

The aim of this paper is to investigate whether weak ties play an important role in providing
information about crime. This in some sense extends the idea of the strength of weak ties in the
labor market put forward by Granovetter (1973, 1983) to the crime market. We first develop a
model where individuals have strong and weak ties and can learn about crime opportunities through
them. We show that there is one equilibrium where no crime is committed and another one where
crime exists in equilibrium. By focussing on the latter, we find that, increasing the percentage
of weak ties, induces more transitions from non-crime to crime and thus the crime rate in the economy
increases.

We then test these predictions using the U.S. National Longitudinal Survey of Adolescent Health
(AddHealth), which contains unique detailed information on friendship relationships among delin-
quent teenagers. This dataset provides information of the best friends of each adolescent (i.e. strong
ties) and we can thus define weak ties as friends of best friends, and friends of friends of best friends,
etc. The interesting aspect of this definition is that it avoids some endogeneity problem because if
individuals choose their best friends they do not obviously choose the friends of their best friends, and even less the friends of friends of their best friends, etc. The theoretical predictions of our model seem to be confirmed by the empirical analysis since weak ties have a positive impact on criminal activities.

References


Appendix 1: Proofs of Propositions in the Theoretical Analysis

Proof of Proposition 1: We establish the proof in two steps. First, Lemma 1 characterizes all steady-state dyad flows. Lemma 2 then provides conditions for their existence.

Lemma 1 There exists at most two different steady-state equilibria: (i) a non-criminal equilibrium $U$ such that $c^* = 0$ and $u^* = 1$, (ii) an interior equilibrium $C$ such that $0 < c^* < 1$ and $0 < u^* < 1$.

Proof. By combining (5) to (8), we easily obtain:

$$c^* = [(1 - \omega + \omega c^*)\lambda + p] \frac{2\omega c^* \lambda}{p^2} d_0^*$$  \hspace{2cm} (17)

We consider two different cases.

(i) If $c^* = 0$, then equation (17) is satisfied. Furthermore, using (5) and (6), this implies that $d_1^* = d_2^* = 0$ and, using (7) and (2), we have $d_0^* = 1/2$ and $u^* = 1$. This is referred to as steady-state $U$ (no crime).

(ii) If $c^* > 0$, then solving equation (17) yields:

$$c^* = \frac{1}{\lambda \omega} \left[ \frac{p^2}{2 \omega \lambda d_0^*} - p \right] - \frac{(1 - \omega)}{\omega}$$

Define $Z = (1 - \omega) / \omega$, $B = p / (\lambda \omega)$. This equation can now be written as:

$$c^* = \frac{B^2}{2d_0^*} - B - Z$$  \hspace{2cm} (18)

Moreover, by combining (5) and (6), we obtain:

$$d_1^* = \frac{2c^*}{B} d_0^* , \quad d_2^* = \frac{(Z + c^*) c^*}{B^2} d_0^*$$  \hspace{2cm} (19)

- Let us first focus on the case where $c^* = 1$. In that case, it has to be that only $d_2$–dyads exist and thus $d_0^* = d_1^* = 0$, which, using (19) implies that: $d_2^* = 0$. So this case is not possible.

- Let us now thus focus on the case: $0 < c^* < 1$ (which implies that $0 < u^* < 1$)

By plugging (18) and (19) in (7) and after some algebra, we obtain that $d_0^*$ solves $\Phi(d_0^*) = 0$ where $\Phi(x)$ is the following second-order polynomial:

$$\Phi(d_0^*) = -\frac{Z}{B} x^2 - \frac{(1 + Z)}{2} x + \left(\frac{B}{2}\right)^2$$  \hspace{2cm} (20)
Lemma 2

(i) The steady-state equilibrium \( U \) always exists.

(iv) The steady-state equilibrium \( C \) exists when \( p < \lambda [\omega + \sqrt{\omega(4 - 3\omega)}]/2 \).

Proof.

(i) In this equilibrium \( c^* = 0 \), which implies that \( h(c) = (1 - \omega) \lambda \) and \( q(c) = 0 \). There are only \( d_0 \)-dyads so all individuals are non-criminals and will never receive a crime offer since \( q(c) = 0 \). So when a \( d_0 \)-dyad is formed it is never destroyed and thus this equilibrium is always sustainable.

(ii) We know from Lemma 1 that a steady-state \( C \) exists and that \( c^* = 1 \). We now have to check that \( c^* > 0 \) and \( 0 < d_0^* < 1/2 \). Let us thus verify whether there exists some \( 0 < d_0^* < 1/2 \) such that \( \Phi(d_0^*) = 0 \), where \( \Phi(\cdot) \) is given by (20). We have \( \Phi(0) = (B/2)^2 > 0 \) and \( \Phi'(0) = -(1 + Z)/2 < 0 \). Therefore, (20) has a unique positive root smaller than \( 1/2 \) if and only if

\[
\Phi(1/2) = \frac{1}{4} \left[ B^2 - (1 + Z) - \frac{Z}{B} \right] = \frac{1}{4} \left[ 1 + \frac{1}{B} \right] (B^2 - B - Z) < 0.
\]

The unique positive solution to \( x^2 - x - Z = 0 \) is \( \left(1 + \sqrt{(4-3\omega)/\omega}\right)/2 \). Then, \( d_0^* < 1/2 \) if and only if \( B < \left[1 + \sqrt{(4-3\omega)/\omega}\right]/2 \), equivalent to:

\[
p < \frac{\lambda}{2} [\omega + \sqrt{\omega(4 - 3\omega)}]
\]

Observe that \( d_0^* < 1/2 \) guarantees that \( c^* > 0 \).

Proof of Proposition 2:

(i) By totally differentiating (11), we obtain:

\[
\frac{\partial d_0^*}{\partial \omega} = \frac{1}{2} \frac{d_0^2}{p} + \frac{1}{\omega^2} d_0 - \frac{p^2}{2 \lambda^2 \omega^3}
\]

and thus

\[
\text{sgn} \frac{\partial d_0^*}{\partial \omega} = \text{sgn} \left[ \frac{1}{p} d_0^2 + \frac{1}{2 \omega^2} d_0 - \frac{p^2}{2 \lambda^2 \omega^3} \right]
\]

Let us study

\[
\Phi(d_0) = \frac{1}{p} d_0^2 + \frac{1}{2 \omega^2} d_0 - \frac{p^2}{2 \lambda^2 \omega^3}
\]

\[
\Phi(0) = -\frac{p^2}{2 \lambda^2 \omega^3} < 0
\]

\[
\Phi'(d_0) = 2 \frac{1}{p} d_0 + \frac{1}{2 \omega^2} > 0 \text{ when } d_0 \geq 0
\]
\[ \Phi''(d_0) = 2 \frac{\lambda}{p} > 0 \]

We have a quadratic function that crosses only once the positive orthant. Let us calculate \( \hat{d}_0 \) the value for which \( \Phi(d_0) \) crosses the \( d_0 \)-axis. For that, we have to solve: \( \Phi(\hat{d}_0) = 0 \). It is easy to verify that:

\[ \hat{d}_0 = \frac{p}{4 \lambda \omega^2} \left( \sqrt{1 + \frac{8 p \omega}{\lambda}} - 1 \right) > 0 \]

It should be clear that if \( \hat{d}_0 < 1/2 \), then \( \Phi(d_0) < 0 \) for \( 0 < d_0 < 1/2 \) and thus \( \frac{\partial \Phi}{\partial \omega} < 0 \). Let us thus check that \( \hat{d}_0 < 1/2 \), which is equivalent to:

\[ \Omega \left( \frac{p}{\lambda} \right) = 2 \left( \frac{p}{\lambda} \right)^3 - \omega \frac{p}{\lambda} - \omega^3 < 0 \]

We have:

\[ \Omega(0) = -\omega^3 \]

\[ \Omega' \left( \frac{p}{\lambda} \right) = 6 \left( \frac{p}{\lambda} \right)^2 - \omega \]

with

\[ \Omega' \left( \frac{p}{\lambda} \right) < 0 \iff \frac{p}{\lambda} < \sqrt[6]{\omega} \]

It is easy to verify that

\[ \sqrt[6]{\omega} < \frac{[\omega + \sqrt{\omega(4 - 3\omega)}]}{2} \]

so that when \( \frac{p}{\lambda} < \sqrt[6]{\omega} \) holds, then (9) also holds.

To summarize, when \( \frac{p}{\lambda} < \sqrt[6]{\omega} \), then \( \hat{d}_0 < 1/2 \) and thus \( \frac{\partial \Phi}{\partial \omega} < 0 \).

(ii) By totally differentiating (10), we obtain:

\[
\frac{\partial c^*}{\partial \omega} = \frac{\partial B}{\partial \omega} \left( \frac{B}{2} - 1 \right) - B^2 \frac{1}{4} \frac{\partial d_0}{\partial \omega} - \frac{\partial Z}{\partial \omega} \\
= \frac{-p}{\lambda \omega^2} \left( \frac{p}{2 \lambda \omega} - 1 \right) - \frac{p^2}{4 \lambda^2 \omega^2} \frac{1}{d_0} \frac{\partial d_0}{\partial \omega} + \frac{1}{\omega^2} \\
= \frac{p}{\lambda \omega^2} - \frac{p^2}{4 \lambda^2 \omega^2} \frac{1}{d_0} \frac{\partial d_0}{\partial \omega} + \frac{1}{\omega^2} - \frac{p^2}{2 \lambda^2 \omega^3} \\
= \frac{1}{\omega^2} \left[ \frac{p}{\lambda} - \frac{p^2}{4 \lambda^2 d_0} \frac{\partial d_0}{\partial \omega} + 1 - \frac{p^2}{2 \lambda^2 \omega} \right] \\
\]

Thus

\[ \frac{\partial c^*}{\partial \omega} > 0 \iff \frac{p}{\lambda} - \frac{p^2}{4 \lambda^2 d_0} \frac{\partial d_0}{\partial \omega} + 1 > \frac{p^2}{2 \lambda^2 \omega} \]

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\[ \Leftrightarrow \frac{p}{\lambda} + 1 > \frac{p^2}{2\lambda^2 \omega} \]

since \( \frac{d\eta}{d\omega} < 0 \). This is equivalent to:

\[ \frac{1}{2\omega} \left( \frac{p}{\lambda} \right)^2 - \frac{p}{\lambda} - 1 < 0 \]

Let us have:

\[ \Xi\left( \frac{p}{\lambda} \right) \equiv \frac{1}{\omega d_0} \left( \frac{p}{\lambda} \right)^2 - \frac{p}{\lambda} - 1 \]

It is easy to verify that:

\[ \Xi(0) = -1 < 0 \]

\[ \Xi'(\frac{p}{\lambda}) = \frac{2}{\omega d_0} \left( \frac{p}{\lambda} \right) - 1 \]

Now, we have:

\[ \Xi'(\frac{p}{\lambda}) < 0 \iff \frac{p}{\lambda} < \frac{\omega d_0}{2} \]

Observe that since \( 0 < d_0 < 1/2 \) and \( 0 < \omega < 1 \),

\[ \frac{\omega d_0}{2} < \sqrt{\frac{\omega}{6}} < \frac{[\omega + \sqrt{\omega(4 - 3\omega)}]}{2} \]

Thus if

\[ \frac{p}{\lambda} < \frac{\omega d_0}{2} \iff d_0^* > \frac{2p}{\omega \lambda} \]

equilibrium \( C \) exists and, for this equilibrium, \( \frac{\partial d_0^*}{\partial \omega} < 0 \) and \( \frac{\partial c^*}{\partial \omega} > 0 \). From (12) and (13), it is easy to see that \( \frac{\partial d_1^*}{\partial \omega} \) and \( \frac{\partial d_2^*}{\partial \omega} \) cannot be signed. □
Appendix 2: Description of control variables

**Individual socio-demographic variables**

- female: dummy variable taking value one if the respondent is female.
- race: race of respondent, coded as 3-category dummies (white, the reference group, Black or African American and other races).
- age: respondents’ age measured in years.
- health status: response to the question "In the last month, how often did a health or emotional problem cause you to miss a day of school", coded as 0= never, 1= just a few times, 2= about once a week, 3= almost every day, 4= every day.
- religion practice: response to the question: "In the past 12 months, how often did you attend religious services", coded as 0= not applicable, 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.
- school attendance: number or years the respondent has been a student at the school.
- student grade: grade of student in the current year.
- mathematics score: score in mathematics at the most recent grading period, coded as 1= D or lower, 2= C, 3=B, 4=A, which is the highest grade.
- organized social participation: dummy taking value one if the respondent participate in any clubs, organizations, or teams at school in the school year.
- motivation in education: dummy taking value one if the respondent reports to try very hard to do his/her school work well, coded as 1= I never try at all, 2= I don’t try very hard, 3= I try hard enough, but not as hard as I could, 4= I try very hard to do my best.
- self esteem: response to the question: "Compared with other people your age, how intelligent are you", coded as 1 = moderately below average, 2 = slightly below average, 3 = about average, 4 = slightly above average, 5 = moderately above average, 6 = extremely above average.
- physical development: response to the question: "How advanced is your physical development compared to other boys your age", coded as 1= I look younger than most, 2= I look younger than some, 3= I look about average, 4= I look older than some, 5= I look older than most.

**Family background variables**

- household size: number of people living in the household.
- public assistance: dummy taking value one if either the father or the mother receives public assistance, such as welfare.
- mother working: dummy taking value one if the mother works for pay.
- two married parent family: dummy taking value one if the respondent lives in a household with two parents (both biological and non biological) that are married.
- single parent family: dummy taking value one if the respondent lives in a household with only one parents (both biological and non biological).
parent education: schooling of (biological or non-biological) parent that is living with the child, coded as 1=never went to school, 2= not graduate from high school, 3= high school graduate, 4=graduated from college or a university, 5= professional training beyond a four-year college. If both parents are in the household, the education of the father is considered.

parents age: mean value of the age of the parents (biological or non-biological) living with the child.

parent occupation: closest description of the job of (biological or non-biological) parent that is living with the child, coded as 9-category dummies (doesn’t work without being disables, the reference group, manager, professional or technical, office or sales worker, manual, military or security, farm or fishery, retired, other). If both parents are in the household, the occupation of the father is considered.

**Protective factors**

parental care: dummy taking value one if the respondent reports that the (biological or non-biological) parent that is living with her/him or at least one of the parents (if both are in the household) cares very much about her/him.

relationship with teachers: dummy taking value one if the respondent reports to have trouble getting along with teachers at least about once a week, since the beginning of the school year.

school attachment: composite score of three items derived from the questions: "How much do you agree or disagree that a) you feel close to people at your school, b) you feel like you are part of your school, c) you are happy to be at your school", all coded as 1= strongly agree, 2= agree, 3=neither agree nor disagree, 4= disagree, 5= strongly disagree. (Crombach-alpha =0.75).

social exclusion: response to the question: "How much do you feel that adults care about you", coded as 1= very much, 2= quite a bit, 3= somewhat, 4= very little, 5= not at all.

**Residential neighborhood variables**

neighborhood quality: interviewer response to the question "How well kept are most of the buildings on the street", coded as 1= very poorly kept (needs major repairs), 2= poorly kept (needs minor repairs), 3= fairly well kept (needs cosmetic work), 4= very well kept.

residential building quality: interviewer response to the question "How well kept is the building in which the respondent lives", coded as 1= very poorly kept (needs major repairs), 2= poorly kept (needs minor repairs), 3= fairly well kept (needs cosmetic work), 4= very well kept.

neighborhood safety: dummy variable taking value one if the interviewer felt concerned for his/her safety when he/she went to the respondent’s home.

residential area type: interviewer’s description of the immediate area or street (one block, both sides) where the respondent lives, coded as 5-category dummies (rural, the reference group, suburban, urban - residential only, 3 or more commercial properties - mostly retail, 3 or more commercial properties - mostly wholesale or industrial, other).
Table 1: Descriptive statistics (9,322 individuals, 166 networks)

<table>
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<th>Mean</th>
<th>St.dev.</th>
<th>Min</th>
<th>Max</th>
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<td>1.22</td>
<td>1</td>
<td>3</td>
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<td>% of weak ties: ( \omega_{i,k}(g_K) )</td>
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<td>0.61</td>
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<td>1</td>
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<tr>
<td>% of weak ties: ( \omega_{i,k}^{[2]}(g_K) )</td>
<td>0.24</td>
<td>0.28</td>
<td>0.11</td>
<td>0.36</td>
</tr>
<tr>
<td>% of weak ties: ( \omega_{i,k}^{[3]}(g_K) )</td>
<td>0.61</td>
<td>0.58</td>
<td>0.04</td>
<td>0.89</td>
</tr>
<tr>
<td>female</td>
<td>0.40</td>
<td>0.34</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>age</td>
<td>15.25</td>
<td>1.85</td>
<td>10</td>
<td>19</td>
</tr>
<tr>
<td>health status</td>
<td>3.03</td>
<td>1.74</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>religion practice</td>
<td>2.69</td>
<td>0.78</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>black or African American</td>
<td>0.20</td>
<td>0.31</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>other races</td>
<td>0.10</td>
<td>0.13</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>school attendance</td>
<td>3.29</td>
<td>1.86</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>student grade</td>
<td>9.24</td>
<td>3.14</td>
<td>6</td>
<td>13</td>
</tr>
<tr>
<td>mathematics score</td>
<td>1.94</td>
<td>1.31</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>organized social participation</td>
<td>0.65</td>
<td>0.20</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>motivation in education:</td>
<td>2.24</td>
<td>0.88</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>relationship with teachers:</td>
<td>0.15</td>
<td>0.35</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>social exclusion:</td>
<td>2.26</td>
<td>1.80</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>school attachment</td>
<td>2.57</td>
<td>1.75</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>parental care</td>
<td>0.65</td>
<td>0.35</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>household size</td>
<td>3.50</td>
<td>1.73</td>
<td>1</td>
<td>6</td>
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<tr>
<td>two married parent family</td>
<td>0.72</td>
<td>0.57</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>single parent family</td>
<td>0.22</td>
<td>0.43</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>public assistance:</td>
<td>0.12</td>
<td>0.16</td>
<td>0</td>
<td>1</td>
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<tr>
<td>mother working</td>
<td>0.64</td>
<td>0.45</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>parent education</td>
<td>3.58</td>
<td>2.08</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>parents age</td>
<td>40.14</td>
<td>13.64</td>
<td>33</td>
<td>75</td>
</tr>
<tr>
<td>parent occupation manager</td>
<td>0.11</td>
<td>0.13</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>parent occupation professional or technical</td>
<td>0.09</td>
<td>0.22</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>parent occupation office or sales worker</td>
<td>0.25</td>
<td>0.29</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>parent occupation manual</td>
<td>0.21</td>
<td>0.30</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>parent occupation military or security</td>
<td>0.08</td>
<td>0.12</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>parent occupation farm or fishery</td>
<td>0.04</td>
<td>0.09</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>parent occupation retired</td>
<td>0.06</td>
<td>0.10</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>parent occupation other</td>
<td>0.13</td>
<td>0.17</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>neighborhood quality</td>
<td>2.95</td>
<td>2.02</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>neighborhood safety</td>
<td>2.96</td>
<td>1.85</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>residential building quality</td>
<td>0.52</td>
<td>0.57</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>residential area type suburban</td>
<td>0.32</td>
<td>0.39</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>residential area type urban - residential only</td>
<td>0.18</td>
<td>0.21</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>residential area type 3 or more commercial properties - mostly retail</td>
<td>0.12</td>
<td>0.15</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>residential area type 3 or more commercial properties - mostly wholesale or industrial</td>
<td>0.13</td>
<td>0.18</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>friend involvement:</td>
<td>1.91</td>
<td>1.59</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>physical development</td>
<td>3.12</td>
<td>2.51</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>self esteem</td>
<td>3.93</td>
<td>1.37</td>
<td>1</td>
<td>6</td>
</tr>
</tbody>
</table>
Table 2: Correlations between weak ties $\omega_{i,k}(g_K)$ and observables

<table>
<thead>
<tr>
<th>Variable</th>
<th>% of weak ties</th>
</tr>
</thead>
<tbody>
<tr>
<td>black or african american</td>
<td>0.0814</td>
</tr>
<tr>
<td>mathematics score</td>
<td>-0.0888</td>
</tr>
<tr>
<td>single parent family</td>
<td>0.0450</td>
</tr>
<tr>
<td>parent education</td>
<td>0.0021</td>
</tr>
<tr>
<td>neighborhood quality</td>
<td>-0.0060</td>
</tr>
<tr>
<td>school catholic or other private with religious affiliation</td>
<td>0.0342</td>
</tr>
<tr>
<td>social isolation indicators:</td>
<td></td>
</tr>
<tr>
<td>self-esteem</td>
<td>0.0545</td>
</tr>
<tr>
<td>physical development</td>
<td>0.0093</td>
</tr>
<tr>
<td>school attachment</td>
<td>0.1003</td>
</tr>
<tr>
<td>social exclusion</td>
<td>0.0234</td>
</tr>
<tr>
<td>symmetric friendship ties</td>
<td>-0.0905</td>
</tr>
</tbody>
</table>
Table 3: Model (16) estimation results – whole sample

<table>
<thead>
<tr>
<th>Dep. var.</th>
<th>Delinquency index</th>
<th>Probability of committing crime</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of weak ties: ( \omega_{i,K}(g_K) )</td>
<td>0.1312*** (0.0217)</td>
<td>0.2054*** (0.0502)</td>
</tr>
<tr>
<td>female</td>
<td>-0.1033** (0.0500)</td>
<td>-0.1338* (0.0637)</td>
</tr>
<tr>
<td>age</td>
<td>0.0322 (0.1021)</td>
<td>0.1311 (0.1212)</td>
</tr>
<tr>
<td>health status</td>
<td>0.1029 (0.2412)</td>
<td>0.1029 (0.2446)</td>
</tr>
<tr>
<td>religion practice</td>
<td>-0.0804*** (0.0257)</td>
<td>-0.2085*** (0.0120)</td>
</tr>
<tr>
<td>black or African American</td>
<td>0.0831** (0.0411)</td>
<td>0.1321*** (0.0411)</td>
</tr>
<tr>
<td>other races</td>
<td>0.1045** (0.0497)</td>
<td>0.0451** (0.0224)</td>
</tr>
<tr>
<td>school attendance</td>
<td>0.0675 (0.2241)</td>
<td>0.1752 (0.2414)</td>
</tr>
<tr>
<td>student grade</td>
<td>-0.0595 (0.0645)</td>
<td>-0.0447 (0.0458)</td>
</tr>
<tr>
<td>mathematics score</td>
<td>-0.2021*** (0.0577)</td>
<td>-0.2288*** (0.0059)</td>
</tr>
<tr>
<td>organized social participation</td>
<td>0.0739 (0.0098)</td>
<td>0.0039 (0.0098)</td>
</tr>
<tr>
<td>motivation in education</td>
<td>-0.9415*** (0.2554)</td>
<td>-0.3407*** (0.0069)</td>
</tr>
<tr>
<td>household size</td>
<td>0.0022** (0.0010)</td>
<td>0.0021** (0.0009)</td>
</tr>
<tr>
<td>two married parent family</td>
<td>-0.5125*** (0.1082)</td>
<td>-0.5150*** (0.0802)</td>
</tr>
<tr>
<td>single parent family</td>
<td>0.6228 (0.6154)</td>
<td>0.2281 (0.1543)</td>
</tr>
<tr>
<td>public assistance</td>
<td>0.3559*** (0.1566)</td>
<td>0.8559*** (0.1661)</td>
</tr>
<tr>
<td>mother working</td>
<td>0.2333 (0.1665)</td>
<td>0.0133 (0.1665)</td>
</tr>
<tr>
<td>parent education</td>
<td>-0.3599*** (0.0707)</td>
<td>-0.1556*** (0.0077)</td>
</tr>
<tr>
<td>parents age</td>
<td>0.0007 (0.1624)</td>
<td>0.0007 (0.1248)</td>
</tr>
<tr>
<td>parent occupation manager</td>
<td>-0.0253 (0.1412)</td>
<td>-0.0253 (0.4128)</td>
</tr>
<tr>
<td>parent occupation professional or technical</td>
<td>-0.0454 (0.5536)</td>
<td>-0.0340 (0.5053)</td>
</tr>
<tr>
<td>parent occupation office or sales worker</td>
<td>0.0067 (0.1409)</td>
<td>0.0075 (0.1499)</td>
</tr>
<tr>
<td>parent occupation manual</td>
<td>0.1066** (0.0505)</td>
<td>0.1106** (0.0515)</td>
</tr>
<tr>
<td>parent occupation military or security</td>
<td>-0.0199 (0.1854)</td>
<td>-0.0719 (0.2185)</td>
</tr>
<tr>
<td>parent occupation farm or fishery</td>
<td>0.0829 (0.4374)</td>
<td>0.0296 (0.3745)</td>
</tr>
<tr>
<td>parent occupation retired</td>
<td>0.2010 (0.2751)</td>
<td>0.0105 (0.2751)</td>
</tr>
<tr>
<td>parent occupation other</td>
<td>0.0312 (0.2556)</td>
<td>0.0312 (0.2551)</td>
</tr>
<tr>
<td>relationship with teachers</td>
<td>0.7293 (0.7254)</td>
<td>0.2930 (0.2504)</td>
</tr>
<tr>
<td>social exclusion</td>
<td>0.4088 (0.4143)</td>
<td>0.0408 (0.1435)</td>
</tr>
<tr>
<td>school attachment</td>
<td>0.2177** (0.1033)</td>
<td>0.0701** (0.0337)</td>
</tr>
<tr>
<td>parental care</td>
<td>-0.7530*** (0.1205)</td>
<td>-0.3001*** (0.0205)</td>
</tr>
<tr>
<td>neighborhood quality</td>
<td>-0.0542 (0.4255)</td>
<td>-0.0542 (0.4255)</td>
</tr>
<tr>
<td>residential building quality</td>
<td>-0.2080*** (0.1003)</td>
<td>-0.0800*** (0.0388)</td>
</tr>
<tr>
<td>neighborhood safety</td>
<td>0.9091*** (0.3005)</td>
<td>0.2991*** (0.0735)</td>
</tr>
<tr>
<td>residential area type suburban</td>
<td>0.0323 (0.2586)</td>
<td>0.1323 (0.5869)</td>
</tr>
<tr>
<td>residential area type urban - residential</td>
<td>-0.1599 (0.4784)</td>
<td>-0.0593 (0.4784)</td>
</tr>
<tr>
<td>residential area type 3 or more commercial properties - mostly retail</td>
<td>0.0070 (0.3666)</td>
<td>0.0706 (0.6666)</td>
</tr>
<tr>
<td>residential area type 3 or more commercial properties - mostly wholesale or industrial</td>
<td>0.0754 (0.7599)</td>
<td>0.1207 (0.7005)</td>
</tr>
<tr>
<td>residential area type other</td>
<td>-0.0098 (0.0682)</td>
<td>-0.0980 (0.4682)</td>
</tr>
<tr>
<td>physical development</td>
<td>0.1423** (0.0693)</td>
<td>0.1542* (0.0956)</td>
</tr>
<tr>
<td>self esteem</td>
<td>0.0901*** (0.0294)</td>
<td>0.1903*** (0.0454)</td>
</tr>
<tr>
<td>school dummies</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>R²</td>
<td>0.5301</td>
<td>0.3599</td>
</tr>
</tbody>
</table>

Notes: Estimated coefficients for the second column and marginal effects for the third column are reported. Robust standard errors adjusted for clustering at the network level are reported in parentheses. One, two, three asterisks indicate statistical significance at the 10, 5, and 1 percent respectively. Regressions are weighted to population proportions.
### Table 4: Model (16) estimation results – different types of crime

<table>
<thead>
<tr>
<th>Type</th>
<th>Probability of committing crime</th>
<th>Delinquency index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type 1</td>
<td>0.4941*** (0.1015)</td>
<td>0.07931***(0.3963)</td>
</tr>
<tr>
<td>% of weak ties: $\omega_{i,\kappa}(g_{\kappa})$</td>
<td>(\kappa)</td>
<td>(\omega)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.4111</td>
<td>.3203</td>
</tr>
<tr>
<td>Type 2</td>
<td>0.1609***(0.0555)</td>
<td>0.2518***(0.2144)</td>
</tr>
<tr>
<td>% of weak ties: $\omega_{i,\kappa}(g_{\kappa})$</td>
<td>(\kappa)</td>
<td>(\omega)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.4013</td>
<td>.3172</td>
</tr>
<tr>
<td>Type 3</td>
<td>0.0885***(0.0164)</td>
<td>0.0762***(0.0199)</td>
</tr>
<tr>
<td>% of weak ties: $\omega_{i,\kappa}(g_{\kappa})$</td>
<td>(\kappa)</td>
<td>(\omega)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.3877</td>
<td>.3002</td>
</tr>
</tbody>
</table>

Notes: Marginal effects for the second and third columns and estimated coefficients for the last column are reported. Robust standard errors adjusted for clustering at the network level are reported in parentheses. One, two, three asterisks indicate statistical significance at the 10, 5, and 1 percent respectively. Regressions are weighted to population proportions. The same control variables as in Table 3 are used.

### Table 5: Model (16) estimation results – split samples

<table>
<thead>
<tr>
<th>Sub-sample (i)</th>
<th>Sub-sample (ii)</th>
<th>Sub-sample (iii)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability of committing crime</td>
<td>Probability of committing crime</td>
<td>Delinquency index</td>
</tr>
<tr>
<td>Probability of committing crime</td>
<td>Probability of committing crime</td>
<td>Delinquency index</td>
</tr>
<tr>
<td>% of weak ties: $\omega_{i,\kappa}(g_{\kappa})$</td>
<td>(\kappa)</td>
<td>(\omega)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.4001</td>
<td>.3199</td>
</tr>
</tbody>
</table>

Notes: Marginal effects for the second and third columns and estimated coefficients for the last column are reported. Robust standard errors adjusted for clustering at the network level are reported in parentheses. One, two, three asterisks indicate statistical significance at the 10, 5, and 1 percent respectively. Regressions are weighted to population proportions. The same control variables as in Table 3 are used.
### Table 6: Robustness checks
#### Model (16) estimation results – whole sample

<table>
<thead>
<tr>
<th>Panel (a)</th>
<th>dep. var. Delinquency index</th>
<th>dep. var. Probability of committing crime</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of weak ties: $\phi_{i,k}^{[2]}(g_K)$</td>
<td>0.5581*** (0.1333)</td>
<td>0.2525*** (0.0755)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.5177</td>
<td>.3311</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel (b)</th>
<th>dep. var. Delinquency index</th>
<th>dep. var. Probability of committing crime</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of weak ties: $\phi_{i,k}^{[2]}(g_K)$</td>
<td>0.1275***(0.0209)</td>
<td>0.1984***(0.0451)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.5293</td>
<td>.3585</td>
</tr>
</tbody>
</table>

Notes: Estimated coefficients for the second column and marginal effects for the third column are reported. Robust standard errors adjusted for clustering at the network level are reported in parentheses. One, two, three asterisks indicate statistical significance at the 10, 5, and 1 percent respectively. Regressions are weighted to population proportions. The same control variables as in Table 3 are used.

### Table 7: Robustness checks
#### Model (16) estimation results – split samples

<table>
<thead>
<tr>
<th>Sub-sample (i)</th>
<th>Sub-sample (ii)</th>
<th>Sub-sample (iii)</th>
</tr>
</thead>
<tbody>
<tr>
<td>dep. var. Probability of committing crime</td>
<td>dep. var. Probability of committing crime</td>
<td>dep. var. Delinquency index</td>
</tr>
<tr>
<td>Panel (a)</td>
<td>Panel (b)</td>
<td>Panel (a)</td>
</tr>
<tr>
<td>% of weak ties: $\phi_{i,k}^{[2]}(g_K)$</td>
<td>% of weak ties: $\phi_{i,k}^{[2]}(g_K)$</td>
<td>% of weak ties: $\phi_{i,k}^{[2]}(g_K)$</td>
</tr>
<tr>
<td>0.1202***(0.0321)</td>
<td>0.3605***(0.1055)</td>
<td>1.2636*** (0.4040)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.3724</td>
<td>.2999</td>
</tr>
</tbody>
</table>

| Panel (b) | Panel (a) | Panel (b) |
| % of weak ties: $\phi_{i,k}^{[2]}(g_K)$ | % of weak ties: $\phi_{i,k}^{[2]}(g_K)$ | % of weak ties: $\phi_{i,k}^{[2]}(g_K)$ |
| 0.0891***(0.0206) | 0.2904***(0.0911) | 0.4807*** (0.1312) |
| $R^2$ | .3909 | .3008 | .5419 |

Notes: Marginal effects for the second and third columns and estimated coefficients for the last column are reported. Robust standard errors adjusted for clustering at the network level are reported in parentheses. One, two, three asterisks indicate statistical significance at the 10, 5, and 1 percent respectively. Regressions are weighted to population proportions. The same control variables as in Table 3 are used.