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The strength of weak ties in crime ☆

Eleonora Patacchini[a], Yves Zenou[b,*]

[a]Facoltà di Scienze Statistiche, Università di Roma "La Sapienza", P.le Aldo Moro, 5, 00185 Rome, Italy
[b]Research Institute of Industrial Economics, Box 55665, 102 15 Stockholm, GAINS and CEPR, Sweden

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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 other peers. 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 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.

JEL classification: A14; K42

Keywords: Peer effects; Network structure; Delinquency

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*Corresponding author. Tel.: +46 86654535; fax: +46 86654599.
E-mail addresses: Eleonora.Patacchini@uniroma1.it (E. Patacchini), yves.zenou@ifn.se (Y. Zenou).

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1. Introduction

Granovetter (1973, 1974, 1983) argued that weak ties[1] 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 network, everyone knows each other, information is shared and so potential sources of information are quickly shaken down, the network 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.[2]

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 develop a theoretical model and test its predictions 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, becoming a criminal and acquiring information about criminal opportunities 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 a *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 17 expert and 17 novice shoplifters during consideration of actual crime opportunities. One aspect that was crucial in differentiating experts from novices

[1]Weak ties are acquaintances and strong ties are close friends.

[2]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.

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, the transmission of criminal information is also 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% increase in the neighborhood juvenile crime rate increases the individual probability to become a delinquent by 2.3%. 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 30–50% of the arrest rate for control groups. This also suggests very strong social interactions in crime behaviors.[3] 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 more general models 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 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,

[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.

[4]Linking social interactions with crime has also been done in dynamic general equilibrium models (İmrohoroğlu et al., 2000; Lochner, 2004) and in search-theoretic frameworks (Burdett et al., 2003, 2004; 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), and Patacchini and Zenou (2005).

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 other peers. 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, as a result, 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 teenagers. This data set 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.

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 data set, 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,[5] 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).

[5] The inner ordering of dyad members does not matter.

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

$$\begin{cases} c(t) = 2d_2(t) + d_1(t), \\ u(t) = 2d_0(t) + d_1(t). \end{cases} \tag{1}$$

The population normalization condition can then be written as

$$c(t) + u(t) = 1 \tag{2}$$

or, alternatively,

$$d_2(t) + d_1(t) + d_0(t) = \tfrac{1}{2}. \tag{3}$$

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/her dyad partner with probability $1 - \omega$, while he/she is matched randomly to any other individual in the population with complementary probability ω.

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 (ω). By definition, weak ties are 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 λ. 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 relative (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 ω.

We denote by p the rate at which criminal are caught. Here, when a criminal is caught, he/she 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 during this period of time.

Flows of dyads between states: It is readily checked that the net flow of dyads from each state between t and $t + \mathrm{d}t$ is given by

$$\begin{cases} \overset{\bullet}{d}_2(t) = h(c(t))d_1(t) - 2pd_2(t), \\ \overset{\bullet}{d}_1(t) = 2g(c(t))d_0(t) - [p + h(c(t))]d_1(t) + 2pd_2(t), \\ \overset{\bullet}{d}_0(t) = pd_1(t) - 2g(c(t))d_0(t), \end{cases} \tag{4}$$

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 (λ 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. Graphical representation is shown in Fig. 1.

For instance, in the first equation, the variation of dyads composed of two criminals $(\overset{\bullet}{d}_2(t))$ is equal to the number of d_1-dyads in which the non-criminal individual has found a crime opportunity (through either his/her strong tie with probability $(1 - \omega)\lambda$ or his/her weak tie with probability $\omega c(t)\lambda$) minus the number of d_2-dyads in which one the two

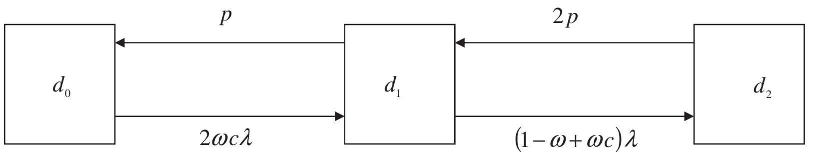

Fig. 1. Flows in the crime market.

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), system (4) reduces to a two-dimensional dynamic system in $d_2(t)$ and $d_1(t)$ given by

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

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:

$$d_2^* = \frac{(1 - \omega + \omega c^*)\lambda}{2p} d_1^*, \tag{5}$$

$$d_1^* = \frac{2\omega c^* \lambda}{p} d_0^*, \tag{6}$$

where

$$d_0^* = \tfrac{1}{2} - d_2^* - d_1^*, \tag{7}$$

$$c^* = 2d_2^* + d_1^*. \tag{8}$$

Definition 1. A steady-state crime equilibrium is a four-tuple $(d_2^*, d_1^*, d_0^*, c^*)$ such that equations (5)–(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* $\mathscr{U}$ *where all individuals are non-criminals and only* d_0*-dyads exist, that is* $d_2^* = d_1^* = c^* = 0$, $d_0^* = \frac{1}{2}$ *and* $c^* = 0$.

(ii) *If*

$$p < \lambda[\omega + \sqrt{\omega(4 - 3\omega)}]/2, \tag{9}$$

there exists a steady-state equilibrium $\mathscr{C}$ *where* $0 < c^* < 1$ *is defined by*

$$c^* = \frac{B^2}{2d_0^*} - B - Z > 0, \tag{10}$$

and $0<d_0^*<\frac{1}{2}$ *is the unique solution of the following equation*:

$$-\frac{Z}{B}d_0^{*2}-\frac{(1+Z)}{2}d_0^*+\left(\frac{B}{2}\right)^2=0. \tag{11}$$

Also, the other dyads are given by

$$d_1^*=\frac{2c^*}{B}d_0^*, \tag{12}$$

$$d_2^*=\frac{(Z+c^*)c^*}{B^2}d_0^*. \tag{13}$$

Proof. See Appendix A.

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 λ, 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 ω on crime. For that, we focus on the interior equilibrium $\mathscr{C}$, defined above, where $0<c^*<1$. We have the following result:

Proposition 2. *Consider the steady-state equilibrium* $\mathscr{C}$ *and assume that* $2p/(\omega\lambda)<d_0^*$. *Then, increasing the percentage of weak ties* ω *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 ω *on* d_1^* *and on* d_2^* *are, however, ambiguous.*

Proof. See Appendix A.

Here, individuals belong to mutually exclusive groups, the dyads, and weak tie interactions spread information across dyads. The parameter ω measures the proportion of social interaction that occurs outside the dyad, the inter-dyad interactions. When ω 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 ω 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 ω on d_2^* and d_1^* is ambiguous. Indeed, from Fig. 1, one can see that individuals leave dyad d_1 and enters dyad d_2 at rate $(1-\omega+\omega c)\lambda$. Now since

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

is ambiguous (because $-1+c^*<0$), the effects mentioned above are also ambiguous. Now consider the effect of ω on d_0^*. This is clearly negative. Indeed, from Fig. 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 ω increases, there are fewer d_0-dyads.

To summarize, the effect of weak ties ω on crime c^* is positive because when ω increases, the transition from non-crime to crime increases since $\partial d_0^*/\partial\omega < 0$, even though we do not know if criminals are more likely to be part of a d_1 or d_2-dyad.

3. Alternative mechanisms

So far, we have put forward the crucial role of information about crime opportunities in explaining the positive relationship between crime rate and the fraction of weak tie dyads. The model provided in the previous section is similar in spirit to many of the job network models (see e.g. Calvó-Armengol and Jackson, 2004) in that individuals pass on information to partners when received. Indeed, having more weak ties increases the range of interactions and information is spread more efficiently and evenly throughout the economy.

In this section, we would like to discuss alternative mechanisms that could give rise to both a positive and negative relationship between crime rate and weak ties.

An increase in weak ties may also lead to a *lowering* of crime rates. Suppose, for instance, that agents share information about both criminal and legitimate (legal) job opportunities. Further suppose that agents only pass on criminal opportunities if they currently do not possess a legitimate job opportunity. In other words, if given a choice between a legitimate job and a criminal opportunity, the individual always chooses a legitimate job opportunity. In this model, the efficient spread of legitimate job opportunities provided by weak ties would compete with the criminal opportunities provided by weak ties. One can then imagine scenarios in such a model where having more weak ties in a network would decrease crime because most agents would have non-criminal possibilities. Alternatively, one could construct an identical model to the one proposed in the previous section by simply re-label crime opportunities with ‘‘non-crime opportunities’’ and conclude that weak ties decrease crime. In this model, one would assume that people commit crime unless they have a non-crime alternative. Weak ties could spread these non-crime alternatives efficiently and reduce crime rates.

These two last mechanisms, though interesting, are, however, not adapted to the delinquency of *teenagers* studied in our empirical analysis below since most of them, who are between 11 and 19 years old, have no labor-market opportunities. To obtain a negative relationship between crime rate and weak ties, one could then consider a model with social sanctions. Indeed, the perception that one's peers will or will not disapprove can exert a stronger influence than does the threat of a formal sanction on whether a person decides to engage in a range of common offences—from larceny, to burglary, to drug use (see, e.g. Braithwaite, 1989; Lott and Mustard, 1997). If a person is surrounded by individuals who are (or appear to be) morally opposed to crime, then he/she is likely to share their aversion. In this context, increasing the presence of weak ties in ego's network increases the percentage of individuals that ego may come into contact with. One possibility then, is that, if someone is labeled a criminal, they may face larger social sanctions if their network contains many weak ties because of the larger number of potential contact partners. On the other hand, these social sanctioning effects may work to *increase* crime if delinquency is seen as a badge of honor in a population (Wilson and Herrnstein, 1985; Kahan, 1997; Silverman, 2004; Ballester et al., 2006). Indeed, when juveniles see others committing crimes, they infer that their peers value law-breaking; they are then more likely to break the law themselves, which leads other juveniles to draw the same inference and engage the same behavior. In this respect, violence and crime can become status-enhancing. As a result, depending whether there are strategic complementarities or substitutabilities in crime, the relationship between crime and weak ties can be positive or negative. Thus there can be social effects (through weak ties) that could increase or decrease the crime rate.

4. Empirical analysis

We now perform an empirical investigation to verify whether the prediction of our model is validated by 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. non-criminals whose best friends are non-criminals) 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. We will also be able to determine whether the other mechanisms highlighted in Section 3, especially the possible negative relationship between crime and weak ties due to sanction effects, are verified or not.

Our empirical strategy is as follows. Using a sample of criminal and non-criminal individuals embedded in friendship networks, and considering network size as a proxy for the number of weak ties, we first directly test the prediction of our model by estimating the correlation between the network crime rate and the network size, while accounting for other relevant variables. Next, we deepen our analysis by exploiting the unique information provided by our data on friendship relationships to construct a proxy of weak ties with individual-level variation. This additional source of variation allows us to control for the possible presence of endogeneity issues such as unobserved heterogeneity both between individuals in the same network and between networks, which might hamper a proper identification of our target effect (these problems are discussed in details in Section 4.2). In short, we first estimate the impact of the individual percentage of weak ties both on the individual level of criminal activity and on the individual probability of committing crime. We then select different sub-samples in order to resemble the different dyadic structures in the theoretical model between each individual and his/her best friends (strong ties) and we investigate whether a change in the individual percentage of weak ties produces an effect in line with the predicted ones.

4.1. Data and definition of variables

Our data source is the National Longitudinal Study of Adolescent Health (AddHealth), which is a study of a nationally representative sample of more than 90,000 adolescents in grades 7–12 in the United States in 1994–1995. The AddHealth website describes surveys and data in details.[6] Besides information on family background, friends, school quality

[6]http://www.cpc.unc.edu/projects/addhealth.

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. The AddHealth contains information on 15 delinquency items.[7] The survey asks students how often they participate in each of the different activities during the past year.[8] 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 variables, a composite score is calculated for each respondent.[9] The mean is 1.03, with considerable variation around this value (the standard deviation is equal to 1.22). The Crombach-α measure is then used to assess the quality of the derived variable. In our case, we obtain an α equal to 0.76 ($0 \leqslant \alpha \leqslant 1$) 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 ω. 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),[10] and this information allows to reconstruct the whole geometric structure of the friendship networks. On average, they declare having 5.04 friends with a noticeable dispersion around this mean value (the standard deviation is equal to 2.32). Our proxy of weak ties ω 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 ω. 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 $\mathbf{g}_\kappa$. We keep track of social connections by a network $\mathbf{g}_\kappa$, 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 $g_{ii,\kappa} = 0$.[11] Assume that there are K network components in the economy,

[7]Namely, paint graffiti or signs on someone else's property or in a public place; deliberately damage property that did not 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.

[8]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.

[9]This is a standard factor analysis, where the factor loadings of the different variables are used to derive the total score.

[10]The limit in the number of nominations is not binding. Less than 1% of the students in our sample show a list of 10 best friends, and less than 15% report five best friends of their own gender.

[11]Thus, 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,

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 $\mathbf{g}_\kappa$ are either directly linked or are indirectly linked through a sequence of agents in $\mathbf{g}_\kappa$. Second, two agents in different network components $\mathbf{g}_\kappa$ and $\mathbf{g}_{\kappa'}$ cannot be connected through any such sequence.

Formally, we define by $\Omega^{\mathrm{S}}_{i,\kappa}$ the number of strong ties of each agent i in network $\mathbf{g}_\kappa$, which is in our data set the number of best friends of i in $\mathbf{g}_\kappa$. We have

$$\Omega^{\mathrm{S}}_{i,\kappa}(\mathbf{g}_\kappa) = \sum_{j=1}^{N} g_{ij,\kappa}.$$

Accordingly, the number of weak ties of each agent i, $\Omega^{\mathrm{W}}_{i,\kappa}$, will be all individuals who are not his/her best friends, that is

$$\Omega^{\mathrm{W}}_{i,\kappa}(\mathbf{g}_\kappa) = n_\kappa - \Omega^{\mathrm{S}}_{i,\kappa}(\mathbf{g}_\kappa) = n_\kappa - \sum_{j=1}^{N} g_{ij,\kappa}.$$

Observe that, by definition of a network component, two individuals in a network component $\mathbf{g}_\kappa$ are either directly linked (strong ties) or are indirectly linked (weak ties) through a sequence of agents in $\mathbf{g}_\kappa$. This is why the number of weak ties is n_κ 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 $\mathbf{g}_\kappa$ is, respectively, given by

$$1 - \omega_{i,\kappa}(\mathbf{g}_\kappa) = \frac{\Omega^{\mathrm{S}}_{i,\kappa}(\mathbf{g}_\kappa)}{n_\kappa} = \frac{\sum_{j=1}^{N} g_{ij,\kappa}}{n_\kappa}, \tag{14}$$

$$\omega_{i,\kappa}(\mathbf{g}_\kappa) = \frac{\Omega^{\mathrm{W}}_{i,\kappa}(\mathbf{g}_\kappa)}{n_\kappa} = \frac{n_\kappa - \sum_{j=1}^{N} g_{ij,\kappa}}{n_\kappa}. \tag{15}$$

Observe that there is a strong exogenous component in this last measure since the friends of friends, etc. of best friends of agent i can be reasonably considered as given for each individual i.[12]

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. The control variables used in the empirical analysis are described in Appendix B. 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 9322 individuals distributed over 166 networks. Table 1 reveals that, for instance, the average student has spent more than 3 years in the school, is fairly motivated in education, has a good relationship with teachers, has parents with at least a high-school degree, and

(*footnote continued*)
in the majority of cases, best friends tend to be in the same school and thus are systematically included in the network.

[12]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 only weak tie friends who are criminals. The results are qualitatively unchanged, although, as expected, the estimated effects are larger in magnitude.

Table 1
Descriptive statistics (9322 individuals, 166 networks)

	Mean	St.dev.	Min	Max
Delinquency index	1.03	1.22	1	3
Nominated friends	5.04	2.82	1	10
Network size	49.48	16.76	18	84
Weak ties: $\omega_{i,\kappa}(g_\kappa)$	0.66	0.61	0	1
Weak ties: $\omega_{i,\kappa}^{[2]}(g_\kappa)$	0.24	0.28	0.11	0.36
Weak ties: $\omega_{i,\kappa}^{[\geqslant 3]}(g_\kappa)$	0.61	0.58	0.4	0.89
Individual socio-demographic variables				
Criminal	0.77	0.35	0	1
Female	0.4	0.34	0	1
Age	15.25	1.85	11	19
Non-white	0.3	0.29	0	1
Religion practice	2.69	0.78	0	4
School attendance	3.29	1.86	1	6
Mathematics score	1.94	1.31	1	4
Organized social participation	0.65	0.2	0	1
Motivation in education	2.24	0.88	1	4
Self-esteem	3.93	1.37	1	6
Physical development	3.12	2.51	1	5
Family background variables				
Household size	3.50	1.73	1	6
Two-married parent family	0.72	0.57	0	1
Single-parent family	0.22	0.43	0	1
Parent education	3.58	2.08	1	5
Parent age	40.14	13.64	33	75
Parent occupation manager	0.11	0.13	0	1
Parent occupation professional	0.34	0.3	0	1
Parent occupation manual	0.21	0.3	0	1
Parent occupation other	0.31	0.19	0	1
Public assistance	0.12	0.16	0	1
Residential neighborhood variables				
Residential building quality	2.96	1.85	1	4
Concern of neighborhood safety	0.52	0.57	0	1
Residential area type sub-urban	0.32	0.39	0	1
Residential area type urban	0.62	0.27	0	1
Protective factors				
Parental care	0.65	0.35	0	1
Relationship with teachers	0.26	0.48	0	1
School attachment	2.57	1.75	1	5
Social exclusion	3.01	1.82	1	5

lives in a fairly well-kept building. Almost 80% of the adolescents live in households with two parents, and in 72% of the cases, parents are married. The proportion of individuals with any delinquency act is 77% on average. Finally, for our variable of interest $\omega_{i,\kappa}(\mathbf{g}_\kappa)$, one can see that, on average, an individual has 66% of his/her friends that are weak ties.

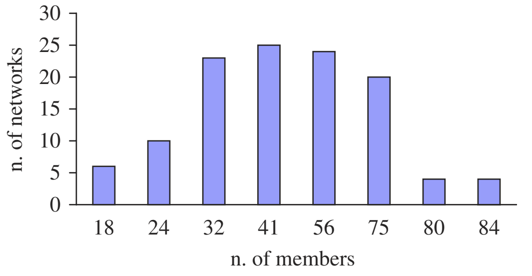

Fig. 2. Empirical distribution of networks by size.

Fig. 2 displays the empirical distribution of network components by their size (i.e. the number of network members).[13] It appears that the distribution is roughly normal and that most friendship networks (roughly 80%) have between 36 and 74 members. The average and the standard deviation of network component size are 49.5 and 16.8, respectively (the median value is 54).[14]

4.2. *Econometric issues and empirical model*

In principle, network size could be considered as a proxy for the number of weak ties: Agents in large networks will have more weak ties than agents in small networks. Thus, a straightforward test of the predictions of our model would be to regress the average crime rate in each network on network size, while controlling for other relevant variables. If we perform such a regression, we obtain a positive and statistical significant OLS estimate of the coefficient of network size,[15] which supports the prediction of our model. Its magnitude is equal to 0.0431, which implies that an increase of five individuals in network size (roughly one-third of its standard deviation) translates into an increase of 0.2155 in the crime rate in aggregate (slightly more than one-fifth of its standard deviation).[16] The effect is not negligible. The question here is that this estimate might be contaminated by endogeneity issues that might hamper a proper identification of our target effect, beginning with a likely endogeneity of network size itself. The availability of individual-level data help us to deal with these issues.

As already highlighted in Section 4.1, our individual-level measure of weak ties may be considered as exogenous for each agent i, given the (indirect) way this measure is constructed.[17] However, a couple of other empirical issues remain to be addressed. Firstly,

[13]The histogram shows on the horizontal axis the percentiles of the empirical distribution of network-component members corresponding to the percentiles 1, 5, 10, 25, 50, 75, 90, 95, 100, and, on the vertical axis, the number of network components having number of members between the ith and $(i-1)$th percentile.

[14]Our analysis has also been performed trimming our sample by eliminating the 5% smaller and bigger networks. The results are qualitatively unchanged. The estimated effects are only slightly reduced in magnitude.

[15]The control set includes age, mathematics score, school attendance, parental education, concern of neighborhood safety and school dummies. It is obtained by averaging the corresponding individual-level variables over network members (see Appendix B for precise definitions of the individual-level counterparts). The complete set of results with all the control variables are available upon request.

[16]The average and standard deviation of the network crime rate (derived by averaging the individual-delinquency index over network members) are 1.11 and 1.01, respectively.

[17]Observe that, by using this variable, 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 with which they are not directly tied to.

we need to rule out the possibility that our measure of weak ties, which is derived 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 rate 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 (like, for example, 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). 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 observables 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. 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 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

Table 2
Correlations between weak ties $\omega_{i,\kappa}(g_\kappa)$ and observables

Variable	Weak ties
Non-white	0.0656
Mathematics score	−0.0888
Single-parent family	0.0450
Parent education	0.0021
Concern of neighborhood safety	−0.0057
School catholic or other private with religious affiliation	0.0342
Social isolation indicators	
Self-esteem	0.0545
Physical development	0.0093
School attachment	0.1003
Social exclusion	0.0234
Symmetric friendship ties	−0.0905

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, $\omega_{i,\kappa} \equiv \omega_{i,\kappa}(\mathbf{g}_\kappa)$, has been separated out from the other explanatory variables for ease of exposition:

$$c_{i,\kappa} = \beta\omega_{i,\kappa} + \sum_{l=1}^{L} \gamma^l x_{i,\kappa}^l + \eta_\kappa + \varepsilon_{i\kappa} \quad \text{for } i = 1, \ldots, N_\kappa;\ \kappa = 1, \ldots, K. \tag{16}$$

Our dependent variable, $c_{i,\kappa}$, is either the level of criminal activity or the probability of committing crime for individual i in network $\mathbf{g}_\kappa$, $x_{i,\kappa}^l$ denotes a set of L control variables for individual i in network $\mathbf{g}_\kappa$, and the error term consists of a network specific component (constant over individuals in the same network), which might be correlated with the regressors, η_κ, 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 an OLS estimator. The estimated value $\widehat{\beta}$ of β measures the empirical impact of percentage of weak ties on criminal outcomes.

4.3. Estimation results

The estimation of model (16) has been performed using different model specifications where different sets of controls have been added (see Appendix B). Table 3 reports the estimation results of the various specifications for our two different dependent variables, $c_{i,\kappa}$, with increasing set of controls across the columns. We start by including, in the first column, standard individuals' characteristics and behavioral factors (i.e. socio-demographic factors, family background, motivation in education, residential neighborhood characteristics and a proxy for individual ability, namely mathematics score). Then, in the second column, we gradually introduce protective factors (i.e. relationship with teachers, social exclusion, school attachment, parental care), and, in the third column, we also control for differences in leadership propensity across teenagers by adding indicators of self-esteem and level of physical development compared to the peers. These are indeed proxies for typically unobserved individual characteristics that may contaminate the estimation of our target coefficient. School dummies are included in all specifications.[18]

The estimated effects of the control variables are qualitatively the same across all model specifications and in line with the expectations. Looking at our target variable, 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 always positive and highly statistically significant. It only slightly decreases in magnitude when more controls are added. 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.

[18]The introduction of student-grade or student-year of attendance dummies does not change qualitatively the results.

Table 3
Model (16) estimation results—whole sample

	(1) Est. coeff.	(1) Est. coeff.	(1) Est. coeff.	(2) Marginal effects	(2) Marginal effects	(2) Marginal effects
Weak ties: $\omega_{i,\kappa}(g_\kappa)$	0.1459*** (0.0322)	0.1382*** (0.0301)	0.1198*** (0.0213)	0.2099*** (0.0533)	0.1963*** (0.0521)	0.1842*** (0.0403)
Female	−0.0973** (0.0445)	−0.1053** (0.0496)	−0.1042** (0.0502)	−0.1313** (0.0637)	−0.1410** (0.0703)	−0.1403* (0.0699)
Age	0.0532 (0.1202)	0.0493 (0.1021)	0.0402 (0.0992)	0.1413 (0.1192)	0.1322 (0.1229)	0.1231 (0.1155)
Non-white	0.0889** (0.0406)	0.0821** (0.0394)	0.0701** (0.0334)	0.1355*** (0.0399)	0.1208*** (0.0304)	0.1035*** (0.0264)
Religion practice	−0.0778*** (0.0195)	−0.0852*** (0.0180)	−0.0877*** (0.0163)	−0.2068*** (0.0371)	−0.2108*** (0.0295)	−0.2208*** (0.0201)
School attendance	0.0767 (0.2255)	0.0702 (0.2188)	0.0607 (0.2124)	0.1887 (0.2434)	0.1775 (0.2124)	0.1605(0.1999)
Mathematics score	−0.2311*** (0.0597)	−0.2289*** (0.0605)	−0.1899*** (0.0507)	−0.2297*** (0.0469)	−0.2221*** (0.0457)	−0.2099*** (0.0305)
Organized social participation	0.0807 (0.1090)	0.0793 (0.0980)	0.0753 (0.0945)	0.0083 (0.0115)	0.0073 (0.0110)	0.0045 (0.0109)
Motivation in education	−0.9645*** (0.2554)	−0.9534*** (0.2297)	−0.9451*** (0.2205)	−0.3497*** (0.0206)	−0.3415*** (0.0125)	−0.3340*** (0.0106)
Self-esteem	–	–	0.1101*** (0.0255)	–	–	0.1789*** (0.0374)
Physical development	–	–	0.1452** (0.0655)	–	–	0.1495** (0.0722)
Household size	0.0022** (0.0010)	0.0021** (0.0009)	0.0020** (0.0010)	0.0022** (0.0009)	0.0022** (0.0010)	0.0021** (0.0010)
Two-married parent family	−0.5225*** (0.1082)	−0.5151*** (0.1080)	−0.5012*** (0.1015)	−0.5359*** (0.1108)	−0.5143*** (0.1065)	−0.5050*** (0.0795)
Single-parent family	0.6122 (0.5461)	0.6212 (0.5430)	0.6125 (0.5161)	0.2463 (0.1675)	0.2228 (0.1540)	0.2332 (0.1550)
Parent education	−0.3895*** (0.0763)	−0.3755*** (0.0717)	−0.3606*** (0.0667)	−0.1855*** (0.0110)	−0.1735*** (0.0105)	−0.1665*** (0.0102)
Parent age	0.0066 (0.1407)	0.0010 (0.1304)	0.0006 (0.1301)	0.0099 (0.1504)	0.0056 (0.1402)	0.0007 (0.1204)
Parent occupation manager	−0.0332 (0.0655)	−0.0301 (0.0594)	−0.0325 (0.0541)	−0.0327 (0.1341)	−0.0329 (0.1315)	−0.0338 (0.1209)
Parent occupation professional	−0.0334 (0.4053)	−0.0394 (0.4550)	−0.0337 (0.4053)	−0.0394 (0.4455)	−0.0334 (0.4153)	−0.0344 (0.4344)
Parent occupation manual	0.1186** (0.0539)	0.1110** (0.0511)	0.1086** (0.0501)	0.1110** (0.0511)	0.1086** (0.0501)	0.1010** (0.0500)
Parent occupation other	0.0282 (0.2121)	0.0255 (0.2005)	0.0231 (0.1882)	0.0275 (0.2141)	0.0273 (0.2114)	0.0255 (0.2115)
Public assistance	0.3785** (0.1720)	0.3654** (0.1660)	0.3412*** (0.1218)	0.8721*** (0.2066)	0.8655*** (0.1856)	0.8455*** (0.1669)
Residential building quality	−0.2069** (0.1092)	−0.2108** (0.1091)	−0.2208** (0.1088)	−0.0725** (0.0335)	−0.0718** (0.0332)	−0.0700** (0.0340)
Concern of neighborhood safety	0.9065*** (0.3010)	0.9129*** (0.3007)	0.9211*** (0.2730)	0.2999*** (0.0597)	0.3199*** (0.0588)	0.3129*** (0.0563)
Residential area type sub-urban	0.0355 (0.2591)	0.0359 (0.2400)	0.0358 (0.2386)	0.1373 (0.5669)	0.1323 (0.5586)	0.1301 (0.5454)

Table 3 (*continued*)

	(1) Est. coeff.	(1) Est. coeff.	(1) Est. coeff.	(2) Marginal effects	(2) Marginal effects	(2) Marginal effects
Residential area type urban	−0.1350 (0.4195)	−0.1301 (0.4017)	−0.1205 (0.3495)	−0.0520 (0.4117)	−0.0505 (0.4105)	−0.0501 (0.4075)
Parental care	–	−0.8001*** (0.1205)	−0.7953*** (0.1120)	–	−0.3305*** (0.0295)	−0.3231*** (0.0203)
Relationship with teachers	–	0.7359 (0.6215)	0.7023 (0.6072)	–	0.2903 (0.2504)	0.2793 (0.2452)
School attachment	–	0.2450** (0.1099)	0.2297** (0.1011)	–	0.0821*** (0.0285)	0.0789*** (0.0273)
Social exclusion	–	0.0450 (0.3940)	0.0422 (0.3741)	–	0.0428 (0.1493)	0.0418 (0.1404)
School dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.5245	0.5274	0.5346	0.3510	0.3569	0.3659

Notes: (1) Dep. var. delinquency index. (2) Dep. var. probability of committing crime. 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%, respectively. Regressions are weighted to population proportions.

Regarding the magnitude of the effects, the positive impact of weak ties on crime is quite small. Specifically, if we consider a change in the percentage of weak ties from two-third (which is the average value of the percentage of weak ties in our sample; see Table 1) to three-quarter, we obtain an increase of the crime index by around 0.012 and an increase in the average probability of committing crime of roughly 0.018%. In light of our discussion in Section 3 on the complicated (potentially opposite) effects of weak ties on crime, large results should not be expected. The fact that (although always small) the impact of weak ties is higher on the probability to commit crime rather than on its level indicates that weak ties seem to be more potent at the extensive rather than intensive margin.

4.3.1. 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 aggregate our list of offences into three groups according to the severity of delinquency behavior. The first group contains the following crimes: (i) painting graffiti or signing on someone else's property or in a public place; (ii) lying to your parents or guardians about where you had been or whom you were with; (iii) running away from home; (iv) acting loud, rowdy, or unruly in a public place. These are referred to as *crimes of type* 1. The second group consists of the following crimes: (i) getting into a serious physical fight; (ii) hurting someone badly enough to need bandages or care from a doctor or nurse; (iii) driving a car without its owner's permission; (iv) stealing something worth less than \$50. These are referred to as *crimes of type* 2. Finally, the third group includes the following crimes: (i) taking something from a store without paying for it; (ii) stealing something worth more than \$50; (iii) going into a house or building to steal something; (iv) using or threaten to use a weapon to get something from someone; (v) selling marijuana or other drugs. These are referred to as *crimes of type* 3. Less than 20% of the teenagers in our sample confess to have committed the more serious offences. We then

Table 4
Model (16) estimation results—different types of crime

	(1) Est. coeff	(2) Marginal effects
Crimes of type 1		
Weak ties: $\omega_{i,\kappa}(g_\kappa)$	0.3489*** (0.0463)	0.4139*** (0.0557)
R^2	0.4199	0.3250
Crimes of type 2	0.1058*** (0.0359)	0.1601*** (0.0433)
Weak ties: $\omega_{i,\kappa}(g_\kappa)$		
R^2	0.4025	0.3179
Crimes of type 3		
Weak ties: $\omega_{i,\kappa}(g_\kappa)$	0.0626** (0.0275)	0.0689*** (0.0203)
R^2	0.3897	0.3077

Notes: (1) Dep. var. delinquency index. (2) Dep. var. probability of committing crime. 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%, respectively. Regressions are weighted to population proportions. The same control variables as in the third specification of Table 3 are used.

perform different estimations of model (16) using as alternative dependent variables the probability of participating (and the intensity of participation) in crimes of type 1, 2, or 3. This approach allows us to obtain different weak tie effects depending on the type of crime committed. The results are contained in Table 4.

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. Specifically, the change in the percentage of weak ties from two-thirds weak ties to three-quarters weak ties raises the average probability of committing crime by more than 0.04% for petty crimes (crimes of type 1) and by less than 0.007% for more serious crimes (crimes of type 3). When we consider the level of criminal activity as the dependent variable, we find a similar decreasing pattern. Not surprisingly, the influence of weak ties friends is stronger for petty crimes than for more serious crimes. This is consistent with the results of Glaeser et al. (1996), who show that social interactions prevail more in petty crimes.

4.3.2. 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 weak ties and individual criminal activity hold true once the structure of the individual percentage of 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 non-criminals) who have most (i.e. more than 60%) 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 non-criminals (sub-sample (ii)). The two sub-samples contain 3,304 and 3,785 individuals respectively.[19]

[19]The remaining 2,233 adolescents 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%, have also been used. The evidences remain

Table 5
Model (16) estimation results—split samples

	Sub-sample (i) Marginal effects	Sub-sample (ii) Marginal effects	Sub-sample (iii) Est. coeff.
Weak ties: $\omega_{i,\kappa}(g_\kappa)$	0.0979*** (0.0309)	0.2903*** (0.1001)	0.4605*** (0.1465)
R^2	0.4015	0.3212	0.5520

Notes: Sub-sample (i) and (ii): Dep. var. probability of committing crime. Sub-sample (iii): Dep. var. delinquency index. 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%, respectively. Regressions are weighted to population proportions. The same control variables as in the third specification of Table 3 are used.

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 2423 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).

The impact of weak ties remains positive and highly statistically significant in all sub-samples. 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 a noticeable impact in raising the probability of committing crime for those having non-criminal strong ties (sub-sample (ii)), whereas the effect is more than two-third smaller for those having criminal best friends (sub-sample (i)). The smaller effect of networks on individuals with criminal best friends is certainly due to the fact that these adolescents are more likely to commit a crime in the first place. Individuals with non-criminal best friends are more on the margin and thus more likely to be affected by the weak tie network effects. Also, consistently with Proposition 2, these results indicate that having more weak ties tends to decrease the number of d_0 dyads since the probability to become a criminal increases.

As expected, 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 much higher than the effect obtained in the whole sample. To be precise, the estimated impact of weak ties is now almost four times bigger (0.4605 in Table 5 versus 0.1198 in Table 3).

4.4. Robustness checks

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

(*footnote continued*)
qualitatively unchanged. We thus present the results obtained using the less stringent value to preserve the sample sizes of our target samples.

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 of meeting 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 on 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_κ as a sequence $\langle i_0, i_1, i_2 \rangle$ of individuals such that $i_0 = i$, $i_1 = k$, $i_2 = j$, with $i_0 \neq i_1 \neq i_2$, and $g_{i_0 i_1,\kappa} = 1$, $g_{i_1 i_2,\kappa} = 1$, that is, individuals i_0 and i_1 as well as i_1 and i_2 are directly linked in g_κ. We denote such a simple path of length 2 between i and j as $g^{[2]}_{ij,\kappa}$. Then, the percentage of weak ties is now defined as

$$\omega^{[2]}_{i,\kappa}(\mathbf{g}_\kappa) = \frac{\sum_{j=1}^{N} g^{[2]}_{ij,\kappa}}{n_\kappa}.$$

Of course now $1 - \omega^{[2]}_{i,\kappa}(\mathbf{g}_\kappa)$ 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 $\omega_{i,\kappa}(\mathbf{g}_\kappa)$. It is easy to see that the use of $\omega^{[2]}_{i,\kappa}(\mathbf{g}_\kappa)$ does not change qualitatively the results (weak ties still have a positive and significant effect on crime), but the estimated effect is always much higher in magnitude.

Our second exercise, instead, consists in using a proxy for weak ties that excludes the friends of length 2. 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 longer 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

$$\omega^{[\geqslant 3]}_{i,\kappa}(\mathbf{g}_\kappa) = \frac{n_\kappa - \sum_{j=1}^{N} g_{ij,\kappa} - \sum_{j=1}^{N} g^{[2]}_{ij,\kappa}}{n_\kappa}.$$

Table 6
Robustness checks: Model (16) estimation results—whole sample

	(1) Est. coeff	(2) Marginal effects
Panel (a)		
Weak ties $\omega^{[2]}_{i,\kappa}(g_\kappa)$	0.2055*** (0.0341)	0.3036*** (0.0615)
R^2	0.5295	0.3595
Panel (b)		
Weak ties: $\omega^{[\geqslant 3]}_{i,\kappa}(g_\kappa)$	0.1115*** (0.0199)	0.1802*** (0.0365)
R^2	0.5308	0.3641

Notes: (1) Dep. var.: delinquency index. (2) Dep. var.: probability of committing crime. 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%, respectively. Regressions are weighted to population proportions. The same control variables as in the third specification of Table 3 are used.

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

	Sub-sample (i) Marginal effects	Sub-sample (ii) Marginal effects	Sub-sample (iii) Est. coeff.
Panel (a)			
Weak ties: $\omega_{i,\kappa}^{[2]}(g_\kappa)$	0.1225*** (0.0339)	0.3617*** (0.1099)	0.4951*** (0.1506)
R^2	0.3837	0.3109	0.5289
Panel (b)			
Weak ties: $\omega_{i,\kappa}^{[\geqslant 3]}(g_\kappa)$	0.0991*** (0.0276)	0.2825*** (0.0901)	0.4701*** (0.1360)
R^2	0.4008	0.3189	0.5440

Notes: Sub-sample (i) and (ii): Dep. var.: probability of committing crime. Sub-sample (iii): Dep. var.: delinquency index. 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%, respectively. Regressions are weighted to population proportions. The same control variables as in the third specification of Table 3 are used.

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 ($\omega_{i,\kappa}(\mathbf{g}_\kappa)$) can be reasonably taken as exogenous.

5. Concluding remarks

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 (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 teenagers. Indeed, this data set 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, even though the magnitude of the effect is quite small.

In Section 3, we propose other mechanisms that can explain a relationship (positive or negative) between crime rate and the percentage of weak ties. However, it has to be acknowledged that the theories focussing on the trade off between labor-market and crime opportunities are not quite applicable to our study since we focus on adolescents that are between 11 and 19 years old and for whom labor-market opportunities are not that relevant. On the other hand, the social theories that involve sanctions and peer effects are much more adequate. Observe that, on average, a criminal has, respectively, 77.6% and 78.1% of his/her best friends and friends (which include both best friends and weak ties of any length) who are criminals. So even if we cannot totally disregard the theory based on social sanctions, the effect should be quite small since criminals are less likely to disapprove their friends' criminal behavior than non-criminals. We are thus left with two possible mechanisms, both based on peer effects and leading to a positive relationship between crime rate and weak ties. The first one, based on the transmission of information between friends, is provided by our theoretical model. The second one is when delinquency is seen as a badge of honor in a population so that committing a crime is a way to be accepted by a local community. Since we find a positive relationship between crime rate and weak ties in our empirical analysis, the peer effect story seems to be confirmed but we are not able to disentangle the two different mechanisms mentioned above. However, since both are based on peer effects (whether peers provide information on crime opportunities or put social pressure to commit crime), some policy implications are quite similar. In particular, an effective policy should not only be measured by the possible crime reduction it implies but also by the group interactions they engender.

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Appendix A. 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* $\mathcal{U}$ *such that* $c^* = 0$ *and* $u^* = 1$, (ii) *an interior equilibrium* $\mathcal{C}$ *such that* $0 < c^* < 1$ *and* $0 < u^* < 1$.

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

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

We consider two different cases.

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

(ii) If $c^* > 0$, then solving Eq. (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

$$c^* = \frac{B^2}{2d_0^*} - B - Z. \tag{18}$$

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

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

- 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:

$$\Phi(d_0^*) = -\frac{Z}{B}x^2 - \frac{(1+Z)}{2}x + \left(\frac{B}{2}\right)^2. \qquad \square \tag{20}$$

Lemma 2. (i) *The steady-state equilibrium $\mathcal{U}$ always exists.*
(ii) *The steady-state equilibrium $\mathcal{C}$ 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 $\mathcal{C}$ exists and that $c^* \neq 1$. We now have to check that $c^* > 0$ and $0 < d_0^* < \frac{1}{2}$. Let us thus verify whether there exists some $0 < d_0^* < \frac{1}{2}$ 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 $\frac{1}{2}$ if and only if

$$\Phi_0(1/2) = \frac{1}{4}\left[B^2 - (1+Z) - \frac{Z}{B}\right] = \frac{1}{4}\left(1 + \frac{1}{B}\right)(B^2 - B - Z) < 0.$$

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

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

Observe that $d_0^* < \frac{1}{2}$ guarantees that $c^* > 0$. $\square$

Proof of Proposition 2. (i) By totally differentiating (11), we obtain

$$\frac{\partial d_0^*}{\partial \omega} = \frac{\frac{\lambda}{p} d_0^{*2} + \frac{1}{2\omega^2} d_0^* - \frac{p^2}{2\lambda^2\omega^3}}{2\frac{\lambda(1-\omega)}{p} d_0^* + \frac{1}{2\omega}},$$

and thus

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

Let us study

$$\Phi(d_0^*) \equiv \frac{\lambda}{p}d_0^{*2} + \frac{1}{2\omega^2}d_0^* - \frac{p^2}{2\lambda^2\omega^3},$$

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

$$\Phi'(d_0^*) = 2\frac{\lambda}{p}d_0^* + \frac{1}{2\omega^2} > 0 \quad \text{when } d_0 \geqslant 0,$$

$$\Phi''(d_0^*) = 2\frac{\lambda}{p} > 0.$$

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

$$\widehat{d}_0^* = \frac{p}{4\lambda\omega^2}\left(\sqrt{1 + \frac{8p\omega}{\lambda}} - 1\right) > 0.$$

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

$$\Omega\left(\frac{p}{\lambda}\right) \equiv 2\left(\frac{p}{\lambda}\right)^3 - \omega\frac{p}{\lambda} - \omega^3 < 0.$$

We have

$$\Omega(0) = -\omega^3,$$

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

with

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

It is easy to verify that

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

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

To summarize, when $p/\lambda < \sqrt{\omega/6}$, then $\widehat{d_0^*} < \frac{1}{2}$ and thus $\partial d_0^*/\partial\omega < 0$.

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

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

Thus

$$\begin{aligned}\frac{\partial c^*}{\partial\omega}>0 &\iff \frac{p}{\lambda}-\frac{p^2}{4\lambda^2}\frac{1}{d_0^*}\frac{\partial d_0^*}{\partial\omega}+1>\frac{p^2}{2\lambda^2\omega}\\ &\iff \frac{p}{\lambda}+1>\frac{p^2}{2\lambda^2\omega},\end{aligned}$$

since $\partial d_0^*/\partial\omega < 0$. 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

$$\Xi(0)=-1<0,$$

$$\Xi'\left(\frac{p}{\lambda}\right)=\frac{2}{\omega d_0^*}\left(\frac{p}{\lambda}\right)-1.$$

Now, we have

$$\Xi'\left(\frac{p}{\lambda}\right)<0 \;\Leftrightarrow\; \frac{p}{\lambda}<\frac{\omega d_0^*}{2}.$$

Observe that since $0<d_0^*<\frac{1}{2}$ and $0<\omega<1$,

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

Thus if

$$\frac{p}{\lambda}<\frac{\omega d_0^*}{2} \;\Leftrightarrow\; d_0^*>\frac{2p}{\omega\lambda}.$$

equilibrium $\mathscr{C}$ exists and, for this equilibrium, $\partial d_0^*/\partial\omega<0$ and $\partial c^*/\partial\omega>0$. From (12) and (13), it is easy to see that $\partial d_1^*/\partial\omega$ and $\partial d_2^*/\partial\omega$ cannot be signed. $\square$

Appendix B. Description of control variables

B.1. Individual socio-demographic variables

Criminal: Dummy variable taking value one if the respondent reports to have committed any crime.

Female: Dummy variable taking value one if the respondent is female.

Age: Age of the respondent measured in years.

Non-white: Dummy variable taking value one if the race of the respondent is non-white.

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 of years the respondent has been a student at the school.

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 variable taking value one if the respondent participates in any clubs, organizations, or teams at school in the school year.

Motivation in education: Response to the question: "How hard do you try to do your 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.

B.2. Family background variables

Household size: Number of people living in the household.

Two-married parent family: Dummy variable 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 variable 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 who is living with the child, coded as 1 = never went to school, 2 = not graduated 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.

Parent 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 the (biological or non-biological) parent who is living with the child, coded as 5-category dummies (does not work without being disable, which is the reference group, manager, professional (or office or sales worker), manual, other). If both parents are in the household, the occupation of the father is considered.

Public assistance: Dummy variable taking value one if either the father or the mother receives public assistance, such as welfare.

B.3. Residential neighborhood variables

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.

Concern of 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 3-category dummies (rural, which is the reference group, sub-urban, urban).

B.4. Protective factors

Parental care: Dummy variable 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 variable 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.

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