THE RESEARCH INSTITUTE OF INDUSTRIAL ECONOMICS

Working Paper No. 645, 2005

Peer Effects and Social Networks in Education and Crime

by Antoni Calvó-Armengol, Eleonora Patacchini and Yves Zenou

IUI, The Research Institute of Industrial Economics
P.O. Box 55665
SE-102 15 Stockholm
Sweden

Peer effects and Social Networks in Education and Crime*

Antoni Calvó-Armengol† Eleonora Patacchini‡ Yves Zenou§

July 5, 2005

Abstract

This paper studies whether structural properties of friendship networks affect individual outcomes in education and crime. We first develop a model that shows that, at the Nash equilibrium, the outcome of each individual embedded in a network is proportional to her Bonacich centrality measure. This measure takes into account both direct and indirect friends of each individual but puts less weight to her distant friends. Using a very detailed dataset of adolescent friendship networks, we show that, after controlling for observable individual characteristics and unobservable network specific factors, the individual's position in a network (as measured by her Bonacich centrality) is a key determinant of her level of activity. A standard deviation increase in the Bonacich centrality increases the level of individual delinquency by 45% of one standard deviation and the pupil school performance by 34% of one standard deviation.

Keywords: Centrality measure, peer influence, network structure, delinquency, school performance.

JEL Classification: A14, I21, K42

*We are grateful to Thierry Magnac and Barbara Petrongolo for helpful comments and suggestions. Financial support from the Fundación Ramón Areces, the Spanish Ministry of Education through grant BEC2002-02130, and the Barcelona Economics Program CREA is gratefully acknowledged by Antoni Calvó-Armengol. Yves Zenou thanks the Marianne and Marcus Wallenberg Foundation for financial support.

†ICREA and Universitat Autònoma de Barcelona, Department of Economics and Economic History, Edifici B, 08193 Bellaterra (Barcelona), Spain, Université de Toulouse and CEPR. Email: antoni.calvo@uab.es

‡Università di Roma "La Sapienza", Facoltà di Scienze Statistiche, Dipartimento di Contabilità Nazionale e Analisi dei Processi Sociali, P.le Aldo Moro, 5, 00185 Rome, Italy. E-mail: Eleonora.Patacchini@uniroma1.it

§IUI, The Research Institute of Industrial Economics, Box 5501, 114 85 Stockholm, Sweden, GAINS (Université du Maine) and CEPR. E-mail: yvesz@iui.se

1 Introduction

It is commonly observed, both in ethnographic and empirical studies, that the behavior of individual agents is affected by that of their peers. This is particularly true in education, crime, labor markets, fertility, participation to welfare programs, etc.[1] The detection and measure of such peer effects is, however, a very difficult exercise. Two main assumptions, not always made explicit, usually accompany this detection and measure. First, peer effects are conceived as an average intra-group externality that affects identically all the members of a given group. Second, the group boundaries for such an homogeneous effect are often arbitrary, and at a quite aggregate level, in part due to the constraints imposed by the available disaggregated data. For instance, peer effects in crime are often measured at the neighborhood level using local crime rates, peer effects in school at the classroom or school level using average school achievements, etc.

In this paper, we propose a theoretical model for peer effects that builds on the smallest unit of analysis for this cross influence, the dyad. The collection of dyadic bilateral relationships constitutes a social network, and our model relates analytically equilibrium behavior to network location. Using a unique dataset of friendship networks from the National Longitudinal Survey of Adolescent Health (AddHealth), we then test the empirical salience of our model predictions. We find that a standard deviation increase in our equilibrium measure of network location accounts for a 45% standard deviation increase in individual delinquency, and a 34% standard deviation increase in pupil school performance.

In what follows, we first describe the theoretical model of peer effects, and then the empirical measure stemming from our theoretical analysis.

Our model starts from a simple premise: peer effects aggregate at the group level the collection of bilateral cross influences the members of this group may or may not exert on each other. Consistent with this approach, the smallest unit of analysis for peer effects is the dyad, a two-person group. The collection of active bilateral influences or dyads constitutes a social network. In this network, each player chooses an optimal level of activity. Individual payoffs then result from the combination of two effects. First, an idiosyncratic component, that decreases marginally in own activity. Second, a peer component, where each agent reaps complementarities from all her dyad partners in the network.

An isolated agent without any dyad partner simply optimizes the idiosyncratic component of her payoff function. This is a single-agent optimal decision problem, with a well-defined maximum.

Consider now an agent who belongs to a network of peer influences. For network connected agents, payoffs are interdependent. We compute the Nash equilibrium of this peer effect game when agents choose their levels of activity simultaneously. At the Nash equilibrium, because of the network complementarities, agents exhaust the marginal returns from their own action above the optimal level of activity for an isolated agent. The actual equilibrium upward shift from this

[1] Durlauf (2004) offers an exhaustive and critical survey.

benchmark value depends, for each agent, on the amount of complementarities accessible to her. Given that complementarities are rooted in direct friendship ties, equilibrium decisions generally differ across agents, and in a manner that reflects the existing heterogeneity in friendship ties. This heterogeneity in friendship ties reflects differences in group exposure across agents, that translate into a population distribution of peer effects. At equilibrium, the group does not exert an average externality common to all group members. Rather, the location of each group member in the network of dyadic influences shapes the strength of the exerted upon externality.[2]

The sociology literature abounds in network measures that assign to each node in a network a different number that quantifies the geometric intricacies of the sub-network surrounding that particular node (Wasserman and Faust, 2004). It turns out from our theoretical analysis that one (and only one) of such network measures captures exactly how each agent subsumes at equilibrium the network payoff complementarities. This is the Bonacich network centrality, due to Philip Bonacich (1989). For a given network, the Bonacich network centrality counts, for each agent, the *total* number of direct and indirect paths of any length in the network stemming from this agent. Such paths are weighted by a geometrically decaying factor (with path length). Therefore, the Bonacich centrality is not parameter free. It depends both on the network topology and on the value of this decaying factor. This has important implications for the empirical analysis that we discuss later.

Our main theoretical result establishes that the peer-effect game has a unique Nash equilibrium in which each agent strategy is proportional to her Bonacich centrality measure. We provide a closed-form expression for this Bonacich-Nash linkage. Furthermore, we show that this equilibrium is in pure strategies and always interior. This Bonacich-Nash linkage holds under a condition that involves the network eigenvalues. This condition guarantees that the level of network complementarities are low enough compared to own-concavity. Under this condition, which is reminiscent but far less demanding that standard dominance diagonal conditions in industrial organization, payoff functions are enough 'concave' so that interiority (and uniqueness) are obtained.[3]

One may wonder why the exact mapping between network location and equilibrium outcome is more intricate than simply counting direct network links, and also requires to account for weighted indirect network links. Recall, indeed, that the payoff interdependence is such that each agent only cares about the behavior of her direct dyad partners. At equilibrium, though, each agent has to anticipate the actual behavior of her dyad partners to take on an optimal action herself. For this reason, every dyad exerts a strategic externality on overlapping dyads, and the equilibrium

[2] Calvó-Armengol and Jackson (2004) describe a network model of information exchange, which opens the black-box of peer effects in drop-out decisions that vary at equilibrium with network location. Ballester *et al.* (2005) provide an exhaustive analysis of a general version of the peer effects game that we discuss here (the case of pure substituability with corner solutions is analyzed in Bramoulle and Kranton, 2005). For literature surveys, see Jackson (2005) on the growing literature on the economics of social networks, and Ioannides and Datcher Loury (2004) on job information networks.

[3] This unique equilibrium is also stable, and thus would naturally emerge from a tatônnement process.

effort levels of each agent must reflect this externality. As a matter of fact, the Bonacich centrality captures adequately how these dyads overlap boils down to an equilibrium (fixed point) pattern of decisions. At equilibrium, individual decisions emanate from all the existing network chains of direct and indirect contacts stemming from each agent, which is a feature characteristic of Bonacich centrality. The parameter that weights paths length has to do with the relative strength of the payoff complementarity compared to own concavity.

That Nash equilibrium behavior can be exactly described by a network measure is very convenient. For instance, the Nash-Bonacich linkage has important implications both for comparative statics and for optimal network policy design (Ballester *et al.* 2005). Here, we explore its empirical validity.

We test the predictions of our peer-effect model by using a very detailed and unique dataset of friendship networks in the United States from the National Longitudinal Survey of Adolescent Health (AddHealth). We explore the role of network location for two different outcomes in which peer effects matter: crime and education. Clearly, a number of empirical issues stemming from endogenous network formation, unobserved individual, school and network heterogeneity might affect our estimation results. The richness of the information provided by the AddHealth data and the use of both within and between network variations allow us to attempt to control for these empirical issues. In particular, the available questions of the AddHealth questionnaire on adolescents' behavior allow us to use observable variables to proxy for unobservable individual heterogeneity (i.e. leadership propensity and ability); the large number of individuals in the survey provides us with enough degrees of freedom to incorporate in the estimation at least school specific dummies, and the large number of networks allows us to use a (pseudo) panel data model specification in order to purge the results from unobservable network-specific (constant across individuals in the same network) effects. Finally, our theoretically driven measure of peers' outcome, which restricts peer influence to interaction with direct friends only, eases off endogeneity issues arising from endogenous network formation. We obtain a clear empirical result: the position of each individual in a network plays an important role in shaping individual behavior.

More precisely, we explore the explanatory power of the Bonacich network centrality on adolescents' delinquency and school performance. For crime, we construct an index of delinquency involvement based on self-reported adolescents' responses to a set of questions describing participation in different criminal activities (15 delinquency items). For education, we construct a school performance index using detailed information on the grade achieved by each student in mathematics, history and social studies and science.

AddHealth contains rich information on friendship networks, which allows us to construct these crime and education indices. Using the in-school friendship nominations data, we obtain a sample of 5,154 criminals distributed over 116 networks, and a sample of 11,964 pupils distributed over 199 networks. Here, we refer to networks as maximally connected components. Within such networks, any agent is directly or indirectly linked to any other one. Across such networks, no network link exists for no pair of agents. For all such networks, we know exactly who is directly linked to whom.

However, the strength of dyadic influences within each network is not readily available in AddHealth. Recall that these parameters enter the calculation of the Bonacich centralities, and correspond to the decaying weights for path length. Using the within network variations, we estimate one different value for the dyadic interaction strength for each network. This estimation uses the first-order conditions of our peer-effect game. Our findings show that the values for the dyadic interaction strength vary widely across networks with their macro topological characteristics. We find a stronger local effect in moderately dense networks with a highly skewed connectivity distribution and a high level of clustering, a characteristic displayed by many real-life networks (Jackson and Rogers, 2004).

The estimated effects of the dyadic interaction strength for the different networks are then used to calculate the individual Bonacich centrality measures of each agent in each network, and to evaluate the impact of this measure on individual outcomes both in education and crime. The Bonacich centrality values we obtain display both within and across network variation. The within network variation is driven by the (potential) structural asymmetry of node locations in each network. The between network variation is driven by the differences in dyadic strength across different networks.

The last stage of our empirical analysis consists in regressing individuals' crime and education outcomes on their corresponding Bonacich network centrality measures and a set of controls. Recall, though, that our theoretical result on the Nash-Bonacich linkage is obtained under some eigenvalue condition on the parameters of the interaction. For the crime data set, there are 28 networks that fail to satisfy this eigenvalue condition (roughly the 24% of the total). Discarding these networks, with a total of 906 people, we are left with a final sample of 4,248 individuals distributed over 88 networks. For the education data set, there are 53 networks that fail to satisfy this condition (roughly the 27% of the total), with a total number of 1,414 discarded people. We get a final sample of 10,550 individuals distributed over 146 networks.

Our estimation results produce a significant estimate of the network location effect, that accounts, respectively, for nearly one half and one third of the variability in crime and education outcomes.

In economics, the influence of peers on individual behavior has been extensively studied. The novelty in our work in threefold. First, from a conceptual point of view, we stress the role of the structure of social networks in explaining individual behavior. Second, from a more operational point of view, we build a theoretical model of peer effects that envisions group influence as an equilibrium outcome by aggregating the collection of active dyadic peer influences. The analysis of such model wedges a bridge between the economics literature, here Nash equilibrium, and the sociology literature, here Bonacich centrality. Third, we conduct an empirical test of our model on the network structure of peer effects using a unique dataset of friendship networks.

In sociology, it has long been recognized that not only friends but also the *structure* of friendship ties are a determinant of individual behavior. The novelty, here, lies in the fact that we model explicitly individual incentives as tailored by the network of relationships, and conduct a full-fledged equilibrium analysis that relates topology to outcome. This equilibrium analysis then guides our empirical analysis. In particular, it singles out the Bonacich network centrality as the adequate topological index to explain outcomes. Besides, our analysis calls for exploiting both within and between network variations to explain behavior.

2 A network model of peer effects

2.1 The model

We develop a network model of peer effects, where the network reflects the collection of active bilateral influences.

The network $N = \{1, \ldots, n\}$ is a finite set of agents. We keep track of social connections by a network $\mathbf{g}$, where $g_{ij} = 1$ if i and j are direct friends, and $g_{ij} = 0$, otherwise. Given that friendship is a reciprocal relationship, we set $g_{ij} = g_{ji}$. We also set $g_{ii} = 0$.

Preferences Each agent i selects an effort $y_i \geq 0$, and obtains a payoff $u_i(\mathbf{y}, \mathbf{g})$ that depends on the effort profile $\mathbf{y} = (y_1, ..., y_n)$ and on the underlying network $\mathbf{g}$, in the following way:

$$u_i(\mathbf{y}, \mathbf{g}) = ay_i - \frac{1}{2}cy_i^2 + d\sum_{j=1}^{n} g_{ij}y_iy_j, \tag{1}$$

where $a, c, d > 0$. Bilateral influences are captured by the following cross derivatives, for $i \neq j$:

$$\frac{\partial^2 u_i(\mathbf{y}, \mathbf{g})}{\partial y_i \partial y_j} = dg_{ij} \geq 0. \tag{2}$$

When i and j are direct friends, the cross derivative is $d > 0$ and reflects a strategic complementarity in efforts. When i and j are not direct friends, this cross derivative is zero.

Note that the utility (1) is concave in own decisions, and displays decreasing marginal returns in own effort levels.

When agents wander in isolation and $\mathbf{g}$ is the empty network, all agents choose the same optimal effort a/c. Otherwise, agents' equilibrium efforts depend on the pattern of bilateral influences reflected in $\mathbf{g}$, and on the intensity of such bilateral influences, captured by d.

For instance, let $n = 2$ and $g_{12} = g_{21} = 1$. When $c < 1$, the equilibrium effort in the dyad is $y_i^* = a/c(1 - d) > a/c$. Each agents reaps complementarities from her dyad partner, and chooses an effort level above the optimal value for an isolated agent.

More generally, local complementarities across directly linked agents in (2) exhaust marginal returns in (1) above the single agent optimum a/c. The actual equilibrium upward shift from this benchmark value a/c depends, for each agent, on the amount of complementarities accessible to him. Given that complementarities are rooted in direct friendship ties, having more friends increases one's effort decision at equilibrium. Equilibrium effort levels thus generally differ across agents, in a manner that reflects the existing heterogeneity in friendship ties.

The exact mapping between network location and equilibrium outcome, though, is more intricate than simply counting direct network links.

Consider for instance the following network with three agents.

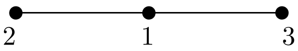

Figure 1. Three agents on a line.

This network results from the overlap between two different dyads with a common partner, agent 1. Agent 2 rips direct complementarities from agent 1 in one dyad whom, in turn, reaps direct complementarities from agents 2 and 3 in both dyads. Thus, through the interaction with the central agent, peripheral agents end up reaping complementarities indirectly from each other. For this reason, the equilibrium decisions in each dyad cannot be analyzed independently of each other. Rather, each dyad exerts a strategic externality on the other one, and the equilibrium effort level of each agent reflects this externality, and the role each agent may play as a driver for the externality.

In what follows, we describe a network centrality measure that turns out to capture exactly how each agent subsumes these strategic externalities across dyads as a function of the location he holds in the network resulting from the dyads' overlap.

2.2 Analysis of the model

We begin by defining a network centrality measure due to Bonacich (1989) that proves fruitful to describe the equilibrium of the peer network model.

The network Bonacich centrality To each network $\mathbf{g}$, we associate its adjacency matrix $\mathbf{G} = [g_{ij}]$. This is a symmetric zero-diagonal square matrix that keeps track of the direct connections in $\mathbf{g}$.

The kth power $\mathbf{G}^k = \mathbf{G}^{(k \overset{times}{\cdots})}\mathbf{G}$ of the adjacency matrix $\mathbf{G}$ keeps track of indirect connections in $\mathbf{g}$. More precisely, the coefficient $g_{ij}^{[k]}$ in the (i, j) cell of $\mathbf{G}^k$ gives the number of paths of length k in $\mathbf{g}$ between i and j. Note that, by definition, a path between i and j needs not to follow the shortest possible route between those agents. For instance, when $g_{ij} = 1$, the sequence $ij \to ji \to ij$ constitutes a path of length three in $\mathbf{g}$ between i and j.

For all integer k, define:

$$b_i^k(\mathbf{g}) = \sum_{j=1}^{n} g_{ij}^{[k]}.$$

This is the sum of all paths of length k in $\mathbf{g}$ starting from i.

Next, let $\phi \geq 0$, and define:

$$b_i(\mathbf{g},\phi) = \sum_{k=0}^{+\infty} \phi^k b_i^k(\mathbf{g}).$$

This is the sum of all paths in $\mathbf{g}$ starting from i, where paths of length k are weighted by the geometrically decaying factor ϕ^k. Note that, for ϕ small enough, this infinite sum takes on a finite value. In matrix notations, we have:

$$\mathbf{b}(\mathbf{g},\phi) = \sum_{k=0}^{+\infty} \phi^k \mathbf{G}^k \cdot \mathbf{1} = [\mathbf{I}-\phi\mathbf{G}]^{-1} \cdot \mathbf{1}, \tag{3}$$

where $\mathbf{1}$ is the vector of ones.

$\mathbf{b}(\mathbf{g},\phi)$ coincides with the vector of network centrality of parameter ϕ in $\mathbf{g}$ first introduced by Bonacich (1987) in sociology. To each agent, it associates a value that counts the *total* number of direct and indirect (weighted) paths in the network stemming from this agent. We refer to $b_i(\mathbf{g},\phi)$ as the Bonacich centrality of agent i in $\mathbf{g}$.

Example 1. Consider the network $\mathbf{g}$ in Figure 1. The corresponding adjacency matrix is,

$$\mathbf{G} = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}.$$

The kth powers of $\mathbf{G}$ are then, for $k \geq 1$:

$$\mathbf{G}^{2k} = \begin{bmatrix} 2^k & 0 & 0 \\ 0 & 2^{k-1} & 2^{k-1} \\ 0 & 2^{k-1} & 2^{k-1} \end{bmatrix} \quad \text{and} \quad \mathbf{G}^{2k+1} = \begin{bmatrix} 0 & 2^k & 2^k \\ 2^k & 0 & 0 \\ 2^k & 0 & 0 \end{bmatrix}.$$

For instance, we deduce from $\mathbf{G}^3$ that there are exactly two paths of length three between agents 1 and 2, which are $12 \to 21 \to 12$ and $12 \to 23 \to 32$. The former path is restricted to the 1-2 dyad, whereas the latter path derives from the dyad overlap and is part of the across-dyads strategic externality.

When ϕ is small enough, the vector of Bonacich network centralities is:

$$\mathbf{b}(\mathbf{g},\phi) = \begin{bmatrix} b_1(\mathbf{g},\phi) \\ b_2(\mathbf{g},\phi) \\ b_3(g,\phi) \end{bmatrix} = \frac{1}{1-2\phi^2} \begin{bmatrix} 1+2\phi \\ 1+\phi \\ 1+\phi \end{bmatrix}.$$

Not surprisingly, agent 1 is more central than agents 2 and 3 and, the more so, the higher ϕ.

Nash equilibrium We now characterize the Nash equilibrium of the game where agents choose their effort level $y_i \geq 0$ simultaneously. When local network complementarities do not offset own decreasing marginal returns, the Nash equilibrium effort decision of each agent is uniquely defined and proportional to her Bonacich network centrality. In other words, Bonacich centrality maps exactly ex ante heterogeneity in network locations into ex post heterogeneity in equilibrium outcomes.

Denote by $\mu_1(\mathbf{G})$ the largest eigenvalue of $\mathbf{G}$.

Proposition 1 *If $d\mu_1(\mathbf{G}) < c$, the peer effect game with payoffs (1) has a unique Nash equilibrium in pure strategies given by:*

$$\mathbf{x}^* = \frac{a}{c}\mathbf{b}\left(\mathbf{g}, \frac{d}{c}\right) \tag{4}$$

Proof. From Theorem 1 in Ballester et al. (2005). ∎

The condition $d\mu_1(\mathbf{G}) < c$ stipulates that local complementarities must be small enough than own concavity, which prevents multiple equilibria to emerge and, in the same time, rules out corner solutions.

Network complementarities are measured by the compound index $d\mu_1(\mathbf{G})$, where d refers to the intensity of each non-zero cross effect, whereas $\mu_1(\mathbf{G})$ refers to the pattern of such cross effects. The largest eigenvalue increases with link addition, so that $\mathbf{G}' \geq \mathbf{G}$ implies $\mu_1(\mathbf{G}') \geq \mu_1(\mathbf{G})$. Therefore, the denser the network of local complementarities, the more stringent the condition in Proposition 1. The highest value for the largest eigenvalue is obtained for the complete network, where every agent is directly linked to every other agent, and is equal to $n-1$. A sufficient condition for the Nash-Bonacich linkage of Proposition 1 to hold is thus $d(n-1) < c$.

Bonacich centrality is the right network index to account for equilibrium behavior. In (1), the local payoff interdependence is restricted to direct network mates. At equilibrium, though, this local payoff interdependence spreads all over the network through the overlap of direct friendship clusters.[4] Bonacich centrality precisely reflects how individual decisions feed into each other along any direct and indirect network path.

Example 2. Consider the network $\mathbf{g}$ in Figure 1. The largest eigenvalue of its adjacency matrix is equal to $\sqrt{2}$. Therefore, when $d\sqrt{2} < c$, the unique Nash equilibrium is:

$$x_1^* = a\frac{c+2d}{c^2-2d^2} \qquad \text{and} \qquad x_2^* = x_3^* = a\frac{c+d}{c^2-2d^2}.$$

The Nash equilibrium effort level increases with group exposure, and is higher for the central agent than for the peripheral ones. Also, the individual exposure to the group influence varies with network location, and the Bonacich centrality captures the variance of peer effects as a function of structural location.

[4] At equilibrium, i's effort decision depends on j's effort decision, for all j such that $g_{ij} = 1$. But j's effort decision depends, in turn, on k's effort decision, for all k such that $g_{jk} = 1$. Therefore, i's decision depends (indirectly) on k's decision, for all k such that $g_{ik}^{[2]} = 1$. And so on.

Network peer effects In this model, the structure of the social network and, in particular, the individual positions in such network, are the main explanatory variables for agents' behavior. This is the Nash-Bonacich linkage. In the crime and education literatures, for instance, social aspects as well as peer effects have been emphasized as important drivers for individual conduct,[5] but seldom from a network perspective.

The novelty of our model lies precisely on the fact that network structural properties become the cornerstone for understanding the influence of peers on individual behavior. In the coming sections, we investigate the empirical relevance of this issue. The empirical measure of peer effects that is derived from our model thus differs substantially from previous work in this area.[6] Indeed, we are not looking at the impact of group peer effects on individual's activity in crime or education. Instead, we consider the impact of the position of each individual in her network of peers (as measured by her Bonacich centrality) on criminal and education outcomes.

3 Data and estimation issues

The aim of our empirical analysis is to explore to which extent the structural position of each individual in a peer network, captured by her Bonacich centrality, accounts for her observed education and crime outcomes. For this purpose, we use a unique data set that provides detailed information on friendship networks within schools in the U.S., the National Longitudinal Study of Adolescent Health (AddHealth).

3.1 Empirical strategy

Guided by Proposition 1, we wish to measure the actual empirical relationship between $b_i(\mathbf{g}, \phi)$ and the observed effort level, y_i^*.

We consider two different individual outcomes for y_i^*, which are: educational achievement and criminal activity. As we discuss below, these are (almost) readily available items in the AddHealth dataset.

To account for these individual outcomes, the main explanatory variable of interest is $b_i(\mathbf{g}, \phi)$, the individual Bonacich centrality of agent i in the peer network $\mathbf{g}$ she belongs to. This explanatory variable is not readily available in the AddHealth dataset. To construct it, we use a two-stage procedure. The first stage provides us with an estimation of ϕ. The second stage regresses y_i^* on the estimated value of $b_i(\mathbf{g}, \phi)$.

First stage: estimation of ϕ We construct $b_i(\mathbf{g}, \phi)$ from two sources of information, the friendship network $\mathbf{g}$ and the parameter ϕ, that measures the strength of the peer influence between any

[5] See, among others, Sah (1991), Glaeser *et al.* (1996), Silverman (2004), for crime, and Bartoleme (1990), Benabou (1993), Epple and Romano (1998), for education. Akerlof (1997) provides a general discussion on these issues.

[6] See, for example, Topa (2001) for an example of an empirical measure of network effects.

two friends in a network.

AddHealth contains rich information on friendship networks, from which we obtain $\mathbf{g}$ directly. The details are discussed below. The value for ϕ, instead, is not readily available in the dataset. The estimation of ϕ is one important aspect that distinguishes our work from previous studies in this area.

Our estimation of ϕ uses the first order conditions of our model of network peer effects.

Assume that there are K network components in the economy. Network components are maximally connected networks, that satisfy the two following conditions. First, two agents 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.

Consider a network component $\mathbf{g}_\kappa$ that connects n_κ different agents. Note that $\sum_{\kappa=1}^{K} n_\kappa = n$.

The preferences of agent i in the network $\mathbf{g}_\kappa$ are given by (1). At equilibrium, each agent maximizes her utility. The corresponding first-order conditions are:

$$\frac{\partial u_{i,\kappa}(\mathbf{y}_\kappa, \mathbf{g}_\kappa)}{\partial y_{i,\kappa}} = a_\kappa - c_\kappa y_{i,\kappa} + d_\kappa \sum_{j=1}^{n_\kappa} g_{ij,\kappa} y_{j,\kappa} = 0.$$

Therefore, for each network component indexed by $\kappa = 1, ..., K$, we have:

$$y_{i,\kappa} = \alpha_\kappa + \phi_\kappa \sum_{j=1}^{n_\kappa} g_{ij,\kappa} y_{j,\kappa},$$

where $\phi_\kappa = d_\kappa / c_\kappa$ and $\alpha_\kappa = a_\kappa / c_\kappa$.

The empirical equivalent of this equation is:

$$y_{i,\kappa} = \alpha_\kappa + \phi_\kappa \sum_{j=1}^{n_\kappa} g_{ij,\kappa} y_{j,\kappa} + \upsilon_{i,\kappa}, \qquad \text{for } i = 1, ..., n_\kappa \text{ ; } \kappa = 1, ..., K. \tag{5}$$

where $y_{i,\kappa}$ is the individual i's level of activity (educational achievement or criminal activity) in the network component k.

In this expression, α_κ is a short-hand for $\sum_{m=1}^{M} \beta_\kappa^m x_{i,\kappa}^m$, where $x_{i,\kappa}^m$ is a set of M control variables accounting for individual, network, family, school and residential neighborhood characteristics, and $\upsilon_{i,k}$ is an error term. The network level controls are all local aggregates, that is, aggregates of the control variables among direct friends in the network, which provide individual level variation. A precise description of all the variables used both for educational achievement and criminal activity are contained in Appendix 1.

We obtain n_κ different equations for each network $\mathbf{g}_\kappa$. We estimate one value of ϕ_κ for each such network. This estimation is obtained by OLS on the pool of all agents, $n = n_1 + ... + n_K$. We use a model specification containing interaction terms between network dummies and individuals' local aggregates. The error term is assumed to be uncorrelated across networks, but not necessarily within network. Standard errors are adjusted for within network heteroskedasticity and autocorrelation.

We obtain K different estimates $\widehat{\phi}_1, ..., \widehat{\phi}_K$ for the strength of local interactions, one value for each network.

Second stage: regression on Bonacich The estimated effects of local interactions in the different networks, $\widehat{\phi}_1, ..., \widehat{\phi}_K$, are then used to calculate the individual Bonacich centrality measures. Observe that the first stage estimation gives rise to an estimated value $\widehat{\phi}_\kappa$ of ϕ_κ for each network component $\mathbf{g}_\kappa$. Variations of $\widehat{\phi}_k$ are thus only between network components. These values are then used to obtain $b_{i,\kappa}(\mathbf{g}_\kappa, \widehat{\phi}_\kappa)$, the estimated Bonacich measures of each agent i in each network $\mathbf{g}_\kappa$. These measures vary across agents and both within and between network components. The within-network component variation is driven by $\mathbf{g}_\kappa$, that is, the (potential) structural asymmetry of node locations in $\mathbf{g}_\kappa$. The between-network components variation is driven by $\widehat{\phi}_\kappa$ and its differences in values across different networks. The aim of the second stage of our empirical strategy is to evaluate the impact of the Bonacich measure on individual outcomes both in education and crime.

In accordance with Proposition 1, we estimate the following model:

$$y_{i,\kappa} = \alpha'_\kappa + \beta\, b_{i,\kappa}(\mathbf{g}_\kappa, \widehat{\phi}_\kappa) + \upsilon'_{i,\kappa}, \qquad \text{for } i = 1, ..., n_\kappa \text{ ; } \kappa = 1, ..., K. \tag{6}$$

Here, α'_k is a set of control variables including a selection of variables considered in (5) and $\upsilon'_{i,\kappa}$ denotes an error term. To account for unobserved network effects, we use a specification of the model with a network specific component of the error term.

A (pseudo) panel data fixed effects estimator is adopted. The estimated value $\widehat{\beta}$ of β measures the empirical impact of network location on education and criminal outcomes. Proposition 1 is empirically validated whenever $\widehat{\beta}$ is significantly different from zero. The value of $\widehat{\beta}$ then measures the exact predictive role of structural network positioning for outcomes.

3.2 Estimation issues

We discuss separately the main estimation issues arising at each of our two-stage procedure.

First-stage estimation We use the observed (estimated) level of local social interactions to test the role of the network geometry in shaping individual outcomes, once networks are formed.

We estimate ϕ_κ from the first order conditions. At first sight, this estimation strategy seems to require that the overall network level of education/crime has to be taken as an exogenous variable with respect to each network member's level of activity. This assumption is, of course, hard to believe, all the more in a model of social interactions.

Here, though, this assumption is less stringent because the peer influence we consider is restricted to interactions with direct friends. For this reason, the regressor used in equation (5) considers (only) local aggregate levels of education/crime, instead of the global network level.[7]

However, to exclude the possibility that the endogeneity of network membership decisions may cause some unobservable group heterogeneity that could affect our results, we address explicitly this issue in our empirical analysis.[8] More precisely, we test for the exogeneity of the local aggregate levels of education/crime with respect to individual levels by instrumenting the local aggregates with their deviations from the network component average.

Formally, denote the local aggregates by $\widetilde{y}_{i,\kappa} = \sum_{j=1}^{n_\kappa} g_{ij,\kappa} y_{j,\kappa}$, i.e. the sum of effort levels of all i's direct friends. Then, the corresponding network component average is:

$$\overline{y}_\kappa = \frac{1}{n_\kappa} \sum_{i=1}^{n_\kappa} \widetilde{y}_{i,\kappa} = \frac{1}{n_\kappa} \sum_{i=1}^{n_\kappa} \sum_{j=1}^{n_\kappa} g_{ij,\kappa} y_{j,\kappa}.$$

The instruments correspond to deviations from the average. Here, $\Delta y_{i,\kappa} = \widetilde{y}_{i,\kappa} - \overline{y}_\kappa$, for $i = 1, ..., n_\kappa$; $\kappa = 1, ..., K$.

By construction, these instruments are correlated with $\widetilde{y}_{i,\kappa}$ but have zero average over each network component, that is:

$$\overline{\Delta y}_\kappa = \frac{1}{n_\kappa} \sum_{i=1}^{n_\kappa} \Delta y_{i,\kappa} = 0, \qquad \text{for } \kappa = 1, ..., K.$$

We use a simple two-step instrumental variable methodology (procedure described in Wooldridge, 2002, p. 474). This procedure consists on estimating an augmented version of model (5):[9]

$$y_{i,\kappa} = \rho_\kappa \widehat{\varepsilon}_{i,\kappa} + \phi_\kappa \widetilde{y}_{i,\kappa} + \upsilon_{i,\kappa}, \qquad \text{for } i = 1, ..., n_\kappa,$$

where the $\widehat{\varepsilon}_{i,\kappa}$ are the estimated residuals of a regression of $\widetilde{y}_{i,\kappa}$ on the set of exogenous variables in model (5) and the instruments $\Delta y_{i,\kappa}$. Using the standard t-test, a failure to reject the hypothesis $H_0 : \rho_\kappa = 0$ indicates that $\widetilde{y}_{i,\kappa}$ can be taken as exogenous variable. In our case, we obtain a t-test statistic for ρ_k equal to 1.31 and 1.22 for education and crime, respectively. Thus, endogeneity issues do not seem to be a major concern for our analysis.

Second-stage estimation In the second-stage estimation, a function of the $\widehat{\phi}_\kappa$s estimated in (5) enters as regressor in (6).[10] Therefore, this two-stage procedure produces consistent estimates

[7] Note that AddHealth provides us with such an impressive amount of information about individuals and friends, that problems of unobserved individual and group effects are less likely to arise.

[8] Beyond network endogeneity, correlated unobservables may arise for other reasons, such as errors-in-variables or contextual variables. See Moffitt (2001) for more details.

[9] Throughout this section, while discussing various versions of models (5) and (6), we drop the set of control variable in their specifications for ease of exposition.

[10] Note that alternative empirical strategies have also been adopted. For instance, a one-step estimation procedure involving *non-linear least squares* produces a similar estimate of β. We choose to report this two-step strategy because it allows us to deal adequately with unobserved network effects that might be relevant in our context.

of β in model (6) provided that $\upsilon_{i,\kappa}$ and $\upsilon'_{i,\kappa}$ are not correlated. If these were so, a correct two-stage estimation only requires a correction of the second stage variance-covariance matrix (see Wooldridge, 2002, p. 116).

Given the tested exogeneity of $\widetilde{y}_{i,\kappa}$ with respect to $\upsilon_{i,\kappa}$, one may reasonably assume straightaway that $\upsilon_{i,\kappa}$ and $\upsilon'_{i,\kappa}$ are, indeed, uncorrelated.

However, one might argue that there may be still some unobserved effects stemming from the individual-network match, which may cause correlation between $\upsilon_{i,\kappa}$ and $\upsilon'_{i,\kappa}$. In order to increase our confidence in our estimation results, we control for this issue in our empirical analysis. This reasoning translates into an error-component version of model (6) with unobserved network effects:

$$y_{i,\kappa} = \eta_\kappa + \beta\, b_{i,\kappa}(\mathbf{g}_\kappa, \widehat{\phi}_\kappa) + \mu_{i,\kappa}, \qquad \text{for } i = 1, ..., n \ ; \ \kappa = 1, ..., K,$$

where the disturbance term consists on a network specific component η_κ, constant over individuals in the same network and correlated with the regressors, and a white noise component, $\mu_{i,\kappa}$.

For network $\mathbf{g}_\kappa$, the resulting model can then be written as:

$$\mathbf{y}_\kappa = \beta\, \mathbf{b}_\kappa(\mathbf{g}_\kappa, \widehat{\phi}_\kappa) + \eta_\kappa \mathbf{1}_\kappa + \boldsymbol{\mu}_\kappa, \tag{7}$$

where variables in bold are vectors of dimension n_κ and $\mathbf{1}_\kappa$ is a vector of ones of same dimension.

When the number of networks is large and there is a fix number of individuals within each network, a pseudo panel data fixed effects estimator can be used to eliminate η_κ from model (7), thus obtaining consistent estimates of β. Provided that the fixed effects transformation of the variables (i.e. deviations form the group mean) is conducted within each network, different network sizes (i.e. different n_κs) are not a matter of concern.

3.3 Data and definition of the dependent variables

Our analysis is made possible by the use of a unique database on friendship networks from the National Longitudinal Survey of Adolescent Health (AddHealth).

The AddHealth database has been designed to study the impact of the social environment (i.e. friends, family, neighborhood and school) on adolescents' behavior in the United States by collecting data on students in grades 7-12 from a nationally representative sample of roughly 130 private and public schools in years 1994-95.

Every pupil attending the sampled schools on the interview-day is asked to compile a brief questionnaire (in-school data) containing questions on respondents' demographic and behavioral characteristics, education, family background and friendship. The AddHealth website describes surveys and data in details.[11] This sample contains information on 90,118 students.

In a second phase of the survey, a subset of adolescents selected from the rosters of the sampled schools is then asked to compile a longer questionnaire containing more sensitive individual and

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

household information (in-home and parental data). This sample contains information on 20,745 students.

Friendship networks AddHealth contains unique detailed information on friendship relationships. This information proves crucial for our analysis. The friendship information is based upon actual friends nominations. Pupils were asked to identify their best friends from a school roster (up to five males and five females). By matching the identification numbers of the friendship nominations to respondents' identification numbers, one can obtain information on the characteristics of nominated friends. Very importantly, one can also reconstruct the whole geometric structure of the friendship network.

For each school, we obtain all the network components of (best) friends.[12] 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. We obtain over two hundred different networks.

We now discuss the data on crime and education.

Criminal activity The in-home questionnaire contains an extensive set of questions on property and violent delinquency, that are used to construct our dependent variable.

By merging the in-school friendship nominations data to the in-home data and by excluding the individuals that report never participating in any delinquent activity (roughly 40% of the total), we obtain a final sample of 5,154 criminals distributed over 116 networks.

The individual level of criminal activity is measured 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 activity.

The AddHealth contains information on 15 delinquency items.[13] The survey asks students how often they participate in each of these activities during the past year. Each response is coded using an ordinal scale ranging from 0 (i.e. never participate) to 1 (i.e. participate 1 or 2 times), 2 (participate 3 or 4 times) up to 3 (i.e. participate 5 or more times). On the basis on these scores, a summated index is calculated for each respondent. The mean is 1.57, with considerable

[12] Thus, in a network component, a link exists between two friends if at least one of the two individuals has identified the other as his/her best friend.

[13] Namely, 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.

variation around this value (the standard deviation is equal to 1.73). The Crombach$-\alpha$ measure is then used to assess the quality of the derived variable. In our case, we obtain an α equal to 0.80 ($0 \leq \alpha \leq 1$) indicating that the 15 different items incorporated in the index have considerable internal consistency. Because we focus our attention only on networks of criminals (i.e. we exclude all respondent having 0 in all items), the distribution of the delinquency index is not far from normal, causing no substantial concerns in the use of the OLS estimation method.

Table 1 provides descriptive statistics on the adolescents selected in our sample of criminals. It reveals that, for instance, the average criminal adolescent is male, white, does not participate regularly to religious services, has a very poor performance at school and a low motivation in education, lives in a poor quality neighborhood and in a poorly kept building, spends a considerable time hanging around with friends, attends a public school where the anti-crime regulations are not so strict and does not feel that adults care very much about him/her. Almost 70% of the adolescents live in households with two parents, but only in the 32% of the cases parents are married, and the most recurrent parent occupation is manual.

[*Insert Table* 1 *here*]

Education achievements The in-home questionnaire contains detailed information on the grade achieved by each student in mathematics, history and social studies and science, ranging from D or lower to A, the highest grade (re-coded 1 to 4). On the bases on these scores, similarly to the construction of the delinquency index, a school performance index is calculated for each respondent. The mean is 2.34 and the standard deviation is equal to 2.11. Also in this case, the distribution of the school performance index is not far from normal. The value of the Crombach-α, which is equal to 0.86, points to the good quality of the derived indicator.

By merging the in-home data to the in-school friendship nominations data and by excluding the individuals that report a non valid answer to the target questions (e.g. didn't take this subject, refused, don't know), we obtain a final sample of 11,964 pupils distributed over 199 networks.

Table 2 provides descriptive statistics on the students selected in this sample. It 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 33% 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.

[*Insert Table* 2 *here*]

4 Empirical results

4.1 Descriptive evidence

Figures 2a and 2b display the empirical distribution of network components by their size (i.e. the number of network members) for all adolescents and for criminals, respectively.[14] From these figures, one can see that both distributions are roughly normal and that most friendship networks have between 30 and 90 members (a little bit less for crime networks). In fact, the minimum number of friends in a network component is 16 for education and 18 for crime, while the maximum is 107 for education and 84 for crime. For education, the average and the standard deviation of network component size are 60.42 and 24.48, respectively, while for crime, these values are 44.43 and 18.34, respectively.

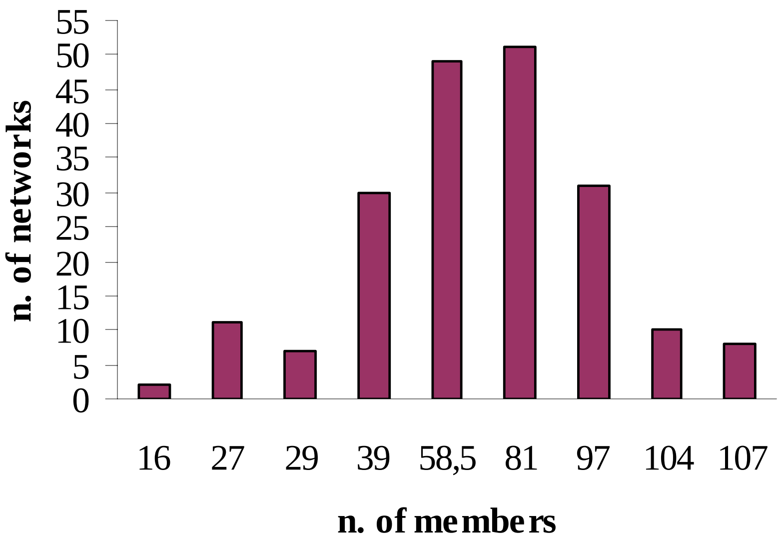

Figure 2a. The empirical distribution of adolescent networks

[14]The histograms show on the horizontal axes the percentiles of the empirical distribution of network component members corresponding to the percentages 1, 5, 10, 25, 50, 75, 90, 95, 100 and in the vertical axes the number of network components having number of members between the i and $i-1$ percentile. For Figure 2b, the 1% and 5% percentiles coincide.

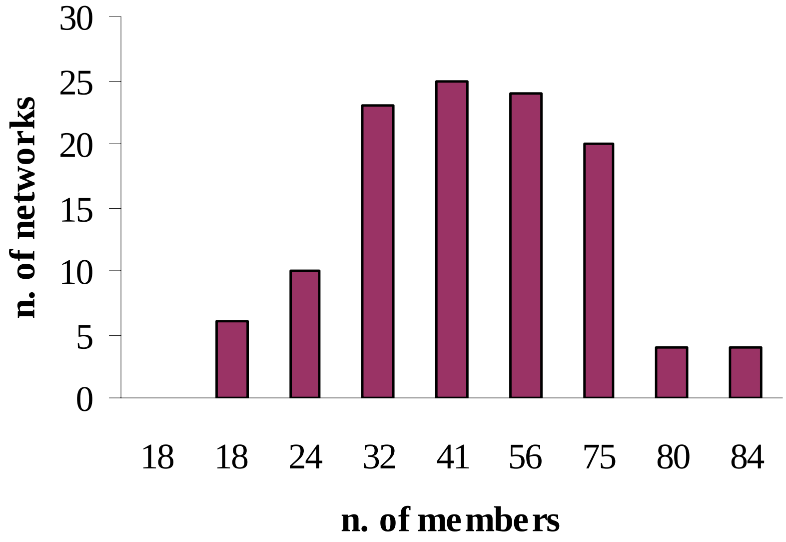

Figure 2b: The empirical distribution of criminal networks

Figure 3 depicts a friendship school network with 16 pupils from the education data set. It is one of the smallest networks in our sample (both for the education and crime data). In this network, the most connected student (number 9) has ten direct friends, and the least connected students (numbers 1, 15 and 16) have only one direct friend. Not surprisingly, agent 9 has also the highest Bonacich centrality measure (equal to 3.40) while agents 1, 15 and 16 have the lowest one (equal to 1.28). This is a maximal network component, so that no student in the network has nominated any student outside the network. The largest network in our sample is almost seven times bigger and has 107 members.

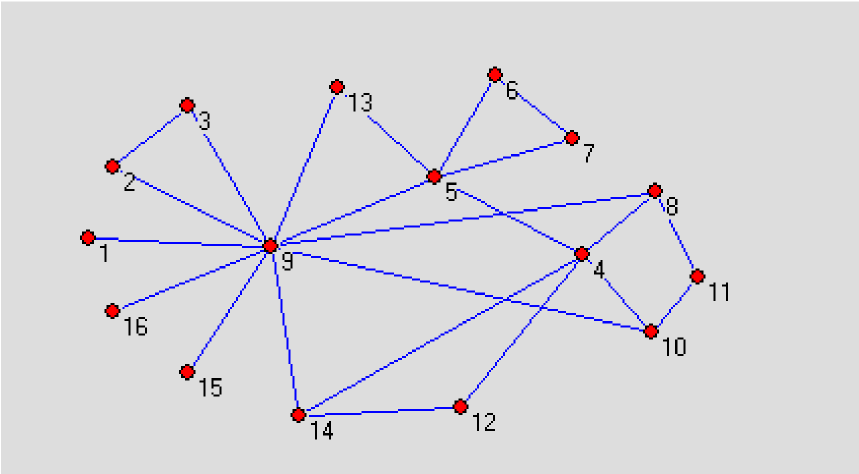

Figure 3. Smallest network of adolescents ($n = 16$)

4.2 Econometric results: first-stage estimation

The estimated ϕ_ks are all highly significant and in the range $0.01 - 1.02$ for crime, and $0.05 - 1.32$ for education.

The average estimate of ϕ, which indicates the extent of social interactions, is equal to 0.58 (with standard deviation 0.59) for crime, and equal to 0.43 (with standard deviation 0.79) for education. In terms of standard deviations, these peer effects translate into roughly an average 20% increase in individual level of delinquency and an average 16% increase in school performance. This is consistent with the empirical studies of social interactions and peer effects in crime (see e.g. Case and Katz, 1991, Glaeser et al., 1996,) and education (see e.g. Evans et al., 1992, Sacerdote, 2001)

The estimated value $\widehat{\phi}_\kappa$ measures the strength of each existing bilateral influence in the network $\mathbf{g}_\kappa$. These estimated values, $\widehat{\phi}_1, ..., \widehat{\phi}_K$, vary widely across the $K = 116$ criminal networks and the $K = 199$ school-peer networks. These differences are partly driven by the structural differences across such networks, as we examine below.

Figures 4a-4c[15] plot the estimated $\widehat{\phi}_k$s (with confidence bands) against three different structural network measures.[16] These measures are density (Figure 4a), asymmetry (Figure 4b) and

[15] Figures 4a-4c relate only to crime data. The education data leads to similar pictures. Thus these graphs are not reported here. They are available upon request.

[16] The $\widehat{\phi}_k$s are normalized to be between 0 and 1, divided in ten intervals and averaged over each interval. The mean values in each interval are displayed on the horizontal axes, while the average structural properties of the corresponding networks are reported on the vertical axes. The confidence bands are based on the derived standard errors of the average estimated levels of $\widehat{\phi}_k$s in each interval, assuming independency of the $\widehat{\phi}_k$s across the different networks.

redundancy (Figure 4c). In Figure 4b and 4c, the $\widehat{\phi}_k$s are divided by the network density.[17]

Network density is simply the fraction of all possible ties present in a network. It ranges from 0 to 1 as networks get denser. Network asymmetry is the ratio of the highest to the lowest node connectivity in a network component. It is related to the variance of connectivities. We normalize it, so that it reaches 1 for the most asymmetric network in the sample. Network redundancy is the fraction of all transitive triads[18] over the total number of triads. It measures the probability with which two of i's friends know each other. Redundancy, or clustering, is much higher in social networks than in randomly generated graphs.[19] Again, we normalize it.

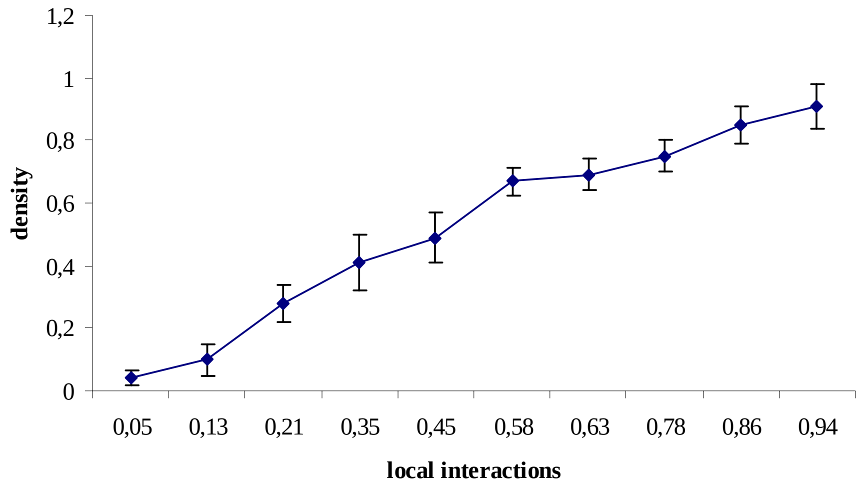

Figure 4a: Density in crime networks

[17] These estimation results refers to the specification of model (5) where a complete set of control variables has been introduced. The inclusion of an increasing number of controls has the effect of only slightly decreasing the extent of the peers effects, but they remain always significant and qualitatively the same. The different sets of controls are a selection of the ones included in the second stage (Table 3) and they show roughly the same effects. Thus, the estimation results for all the other control variables of this first stage are not reported here for ease of brevity.

[18] A triad is the subgraph on three individuals, so that when studying triads, one has to consider the threesome of individuals and all the links between them. A triad involving individuals i, j, k is transitive if whenever $i \to j$ and $j \to k$, then $i \to k$.

[19] See Jackson and Rogers (2004) for more details.

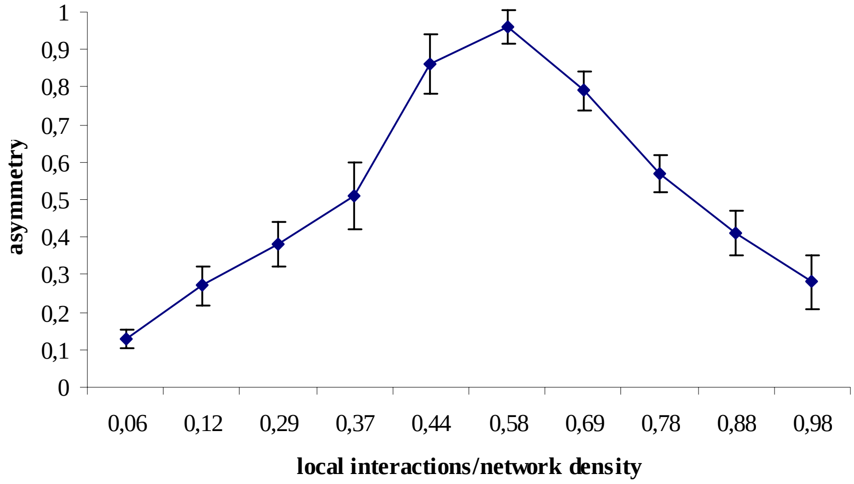

Figure 4b: Asymmetry in crime networks

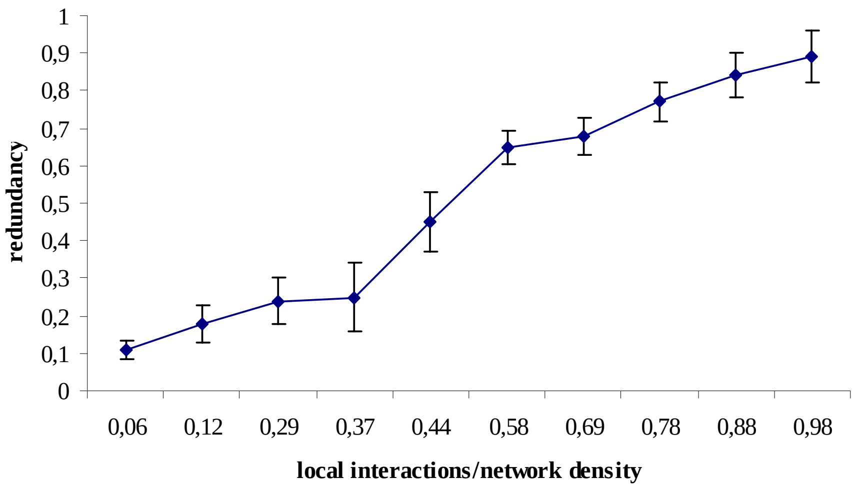

Figure 4c: Redundancy in crime networks

Figure 4a shows that the strength of bilateral influences increases steadily with network density for low values, and remains roughly unchanged for higher values. Therefore, richer networks are a sign of stronger dyadic cross effects, at least until roughly 60% of all possible networks links are created. Figure 4b shows that network asymmetry has a non-trivial impact on the intensity of peer effects. Highly distributed and symmetric networks are compatible with both very low and very high values of the peer-to-density ratio, while highly centralized and asymmetric networks are always synonymous of an average value of peer effects. Finally, Figure 4c shows that link redundancy, or clustering, has a strong positive impact on the strength of bilateral influences above a minimum threshold value.

Altogether, these figures suggest that peer effects are strong in moderately dense networks displaying a highly skewed connectivity distribution and a high level of clustering. This is, in fact, the footprint of most real-life large scale social networks (Jackson and Rogers, 2004). Peer effects can also be strong in dense and distributed networks with high clustering. Instead, peer effects are always low in sparse and distributed networks with low clustering. High clustering, therefore, is a necessary condition for strong peer effects.

4.3 Econometric results: second-stage estimation

The Nash-Bonacich linkage in Proposition 1 holds when $\phi\mu_1(\mathbf{g}) < 1$, where $\mu_1(\mathbf{g})$ is the largest eigenvalue of the adjacency matrix associated to $\mathbf{g}$. For our empirical analysis, we thus discard all those networks $\mathbf{g}_\kappa$ for which the value of ϕ_κ obtained after the first-stage estimation is higher than the inverse of the largest eigenvalue of $\mathbf{g}_\kappa$.

For example, for the student network component in Figure 3, the estimated value for ϕ is 0.5 (with standard deviation 0.5010). The largest eigenvalue for this network is 7.15, and its inverse is equal to 0.14. The Bonacich-Nash linkage thus holds for this network. The estimated values for Bonacich range from 1.04 to 3.40. The Bonacich centrality for the least connected student is equal to 1.2852. The least connected student does not coincide with the least central one. One student with twice as much contacts than the least connected one is the least central in the group. Instead, in this case, the most connected student is also the most central one.

For the crime data set, there are 28 networks that fail to satisfy the eigenvalue condition (roughly the 24% of the total), with a total number of 906 discarded people. We are left with a final sample of 4,248 individuals distributed over 88 networks. For the education data set, there are 53 networks that fail to satisfy this condition (roughly the 27% of the total), with a total number of 1,414 discarded people. We get a final sample of 10,550 individuals distributed over 146 networks.

For these subsamples, we use the estimated $\widehat{\phi}_\kappa$s to calculate the Bonacich measure $b_{i\kappa}(\mathbf{g}_\kappa, \widehat{\phi}_\kappa)$ for each individual $i = 1, ..., n_\kappa$ in each network $\kappa = 1, ..., K$. The Bonacich measures range between 1.09 and 4.79, with an average of 2.69 and a standard deviation of 2.05 for the crime data, and between 1.02 and 5.91 with an average of 2.18 and a standard deviation of 2.58 for the education data.[20]

The estimation of model (7), both with the crime and education data, has been performed using different model specifications where different sets of controls have been added (see Appendix

[20] Note that the theory implies that the Bonacich measures have to be strictly greater than 1 (it is equal to 1 if $\phi = 0$).

1). We start by including standard individuals' characteristics and behavioral factors (i.e., socio-demografic 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. We then include proxies aiming at capturing the quality of social interactions: individual behavior towards friends in general and characteristics of local interactions, related both to the individual behavior towards direct friends and to derived characteristics of direct friends.

Finally, we also attempt to control for unobservable individual and school characteristics that may be correlated with our variable of interest. Regarding criminal behavior, it is sensible to think that probably more self-confident and more motivated individuals end up to be leaders, thus showing a higher value of the Bonacich measure. If these individuals are also more likely to commit crime, we then deal with unobservable individual characteristics that may cause criminal outcomes not directly caused by the centrality measure. Technically, there may exist a positive correlation between $b_{i,k}(\mathbf{g}_k, \widehat{\phi}_k)$ and $\upsilon'_{i,k}$ that biases OLS estimates upwards. To control for differences in leadership propensity across criminals, we use a proxy of self esteem and the level of physical development compared to the peers. Regarding students' school performance, one might argue that more able and thus more successful students are contacted by a larger number of friends. This also might cause an upward bias in the OLS estimation results. Even though a proxy for individual ability, namely mathematics score, is already included in the set of explanatory variables, we also use the indicator of self-esteem in the education-peer association analysis as a further control for individual unobservable characteristics because more able and thus more successful students are likely to consider themselves as more intelligent than their peers. Similar reasonings apply for possible correlations between our centrality measure and unobservable school characteristics affecting structure and/or quality of school-friendship networks in analyzing both criminal behavior and school performance. Thus, we include school dummies to account for school-specific unobservable effects.[21]

Table 3 reports the estimation results of the final specification of model (7), which include a complete set of controls, both for crime (column two) and education (column three). The estimated effects of the control variables are qualitatively the same across all model specifications and in line with the expectations both in the crime and education results.[22]

[*Insert Table* 3 *here*]

The estimated effects of our Bonacich centrality measure β *in shaping criminal and educational*

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

[22] The complete list of estimation results for all the variables across the different model specification, both for crime and education, are available upon request.

behavior (first row in Table 3) are highly statistically significant in all model specifications, both in the crime and education regressions. These evidence indicates that, after accounting for the effects of an extensive set of observable individual characteristics and unobservable network specific factors, the individual position in the network is key to determine the individual level of criminal activity and school performance.

Regarding the magnitude of the effect, the responsiveness of our dependent variable with respect to the Bonacich centrality measure is considerable. *A standard deviation increase in the Bonacich measure raises the level of individual delinquency by roughly 45% of one standard deviation and the level of student school performance by roughly 34% of one standard deviation.* Bonacich centrality thus accounts for nearly one half of the observed heterogeneity in criminal outcomes, and for one third of the observed variability in educational achievements.

The analysis on the crime data has also been performed using as dependent variables the different types of criminal activities separately. The estimated impact of the Bonacich measure is statistically significant in all cases and, in terms of standard deviations, its magnitude ranges from 16% increase for "use or threaten to use a weapon" to roughly 55% for "get into a serious physical fight". Not surprisingly, the influence of friends is stronger for the latter type of crime than the former.[23] The analysis on the education data has also been performed using as dependent variables mathematics, history and social studies, and science scores separately. Although the impact of the Bonacich measure is much smaller when using mathematics score only, the effects measured in terms of standard deviations are never smaller than 27%.

This evidence provides a powerful test of our theoretical model on the network structure of peer effects. The important insight of this empirical investigation is that, as predicted by the theoretical model, the network structure of friendship relations seems to play a central role in shaping individual decisions and therefore it has to be incorporated into empirical and/or theoretical models seeking to investigate individuals' behavior. It seems also that the magnitude of peer and network effects are stronger in crime than in education. This is not surprising since it is well-established that crime is, to some extent, a group phenomenon, and the source of crime and delinquency is located in the intimate social networks of individuals (see e.g. Sutherland, 1947, Warr, 2002, Calvó-Armengol and Zenou, 2004). Instead, school behavior, although partly subject to peer pressure, is also driven by the institutional role of the school.

It is useful to discuss our results with that of Haynie (2001), who has previously analyzed the delinquency-peer association using Bonacich centrality with the AddHealth database. Her analysis, though, does not follow from an equilibrium analysis, nor does the estimation use first-order conditions. This entails two main differences with respect to our paper. First, her analysis does not restrict to the network of delinquents. The sampled networks mix both delinquents and

[23] This is also consistent with the indirect inference on the role of social interactions in different type of criminal activities provided in Glaeser *et al.* (1996).

non-delinquents adolescent, and centrality in this larger network can hardly be interpreted as a proxy for peer effects. Second, across network variations are not used, and the parameter of dyadic peer strength is fixed (arbitrarily) constant at 0.1 for all networks. For this reason, the role of structural location in explaining outcomes is not very different than the one delivered by other arbitrary measures of network location (like for example the betweenness centrality measure that we describe in the next section).

4.4 An alternative measure of network centrality: betweenness

Our model of network interactions points at the Bonacich centrality as the relevant network measure to account for observed criminal and educational outcomes. Over the past years, social network theorists have proposed a number of centrality measures to account for the variability in network location across agents (Wasserman and Faust, 1994). Roughly, these indices encompass two dimensions of centrality, connectivity and betweenness. The simplest index of connectivity is the number of direct links stemming from each node in the network. Instead, betweenness indexes derive from the number of optimal paths across (or from) every node.[24] Bonacich centrality is an index of connectivity since it counts the number of *any* path stemming from a given node, not just optimal paths.[25] While these measures are mainly geometric in nature, our theory provides a behavioral foundation to the Bonacich centrality measure (and only this one) that coincides with the unique Nash equilibrium of a non-cooperative peer effects game on a social network.

For robustness check, we test the explanatory value of an alternative centrality measure. We use betweenness centrality. This is a very popular network measure that, to our knowledge, lacks any behavioral (nor axiomatic) grounding. Freeman (1978/79) defines the betweenness centrality measure of agent i in a network component $\mathbf{g}_\kappa$ the following way:

$$f_i(\mathbf{g}_\kappa) = \sum_{j<l} \frac{\#\text{ of shortest paths between } j \text{ and } l \text{ through } i \text{ in } \mathbf{g}_\kappa}{\#\text{ of shortest paths between } j \text{ and } l \text{ in } \mathbf{g}_\kappa}$$

Friendships networks are, by definition, undirected networks, where relationships are reciprocal, $g_{ij,\kappa} = g_{ji,\kappa}$. For undirected networks, a normalized version of this measure is:

$$f_i^*(\mathbf{g}_\kappa) = \frac{f_i(\mathbf{g}_\kappa)}{(n_\kappa - 1)(n_\kappa - 2)/2},$$

where n_κ is the size of the network component $\mathbf{g}_\kappa$.

We estimate model (7) using this measure of betweenness. Note that betweenness is a parameter-free network measure, and only one stage of estimation is required (second stage of our empirical analysis). The results are given in Table 4.

[24] See Freeman (1978/79) for an example of betweenness centrality, equal to the mean of the shortest-path distance between some given node and all other nodes that can be reached in the network.

[25] See Borgatti (2003) for a discussion on the lack of a systematic criterium to pick up the "right" network centrality measure for each particular situation.

[*Insert Table 4 here*]

The normalized betweenness measure f_i^* has a mean equal to 0.43 and a standard deviation equal to 0.49 for crime, whereas its mean and standard deviations are equal to 0.45 and 0.51 for education. Looking at the responsiveness of our dependent variables, the estimation results in Table 4 reveal that a standard deviation increase in the betweenness measure raises the level of individual delinquency and school performance by only 11% and 9% respectively. The magnitude of these effects is four times smaller than the estimated impact of the Bonacich centrality measure, evaluated to 45% for crime and 34% education.

There are two main explanations for the discrepancy in the explanatory power of betweenness centrality versus that of Bonacich centrality.

The first reason is that the unique Nash equilibrium of a peer effects game is described exactly by the Bonacich centrality network measure. Bonacich centrality is not an arbitrary network measure to try and describe the structural role of network positioning on individual behavior in the presence of local complementarities. Rather, it results from a positive analysis that maps network topology to equilibrium behavior. The closed-form expression of this mapping gives rise exactly to an affine transformation of Bonacich centrality. Instead, to our knowledge, betweenness centrality lacks any behavioral nor axiomatic grounding. It is just an ad hoc choice for a network measure to try and grasp how topology shapes behavior, with no a priori connection with the sort of complementarities in decisions characteristic of peer effects.

The second reason is that betweenness centrality is a parameter-free network index. It only depends on the network geometry. Instead, Bonacich centrality depends both on the network topology and on the prevailing peer effect strength inside the group under consideration. Consider a group of agents connected through a network. Fix the average intra-group externality for this group of agents to a certain level. Bonacich centrality keeps track of the relative exposure of every group member to this average influence of the group as a whole. By so doing, the Bonacich centrality distributes unevenly this intra-group average externality across group members. Two agents holding interchangeable locations in two networks with identical geometry but different value for the corresponding average intra-group externality are thus assigned different Bonacich centralities. Instead, these two agents have identical betweenness index. betweenness centrality depends only on the network geometry, but not on the strength of the average peer effect. As such, it leads to the same values for two networks with identical geometric structure even though these networks may be connecting different people, more or less influenced by peer pressure. In other words, betweenness centrality only reflects within-network variations, whereas Bonacich centrality captures both within-network structural variations, and across-networks group differences.

References

[1] Akerlof, G.A. (1997), "Social distance and social decisions," *Econometrica* 65, 1005-1027.

[2] Ballester, C., Calvó-Armengol, A. and Y. Zenou (2005), "Who's who in networks. Wanted: The key player," Unpublished manuscript.

[3] Bartoleme, C.A.M. de (1990), "Equilibrium and inefficiency in a community model with peer group effects," *Journal of Political Economy* 98, 110-133.

[4] Benabou, R. (1993), "Workings of a city: Location, education and production," *Quarterly Journal of Economics* 108, 619-652.

[5] Bonacich, P. (1987), "Power and centrality: A family of measures," *American Journal of Sociology* 92, 1170-1182.

[6] Borgatti, S.P. (2003), "The key player problem," in *Dynamic Social Network Modeling and Analysis: Workshop Summary and Papers*, ed. by R. Breiger, K. Carley and P. Pattison, Committee on Human Factors, National Research Council, pp. 241-252.

[7] Bramoulle, Y. and R. Kranton (2005), "Strategic experimentation in networks," Unpublished manuscript, University of Maryland.

[8] Calvó-Armengol, A. and M.O. Jackson (2004), "The effects of social networks on employment and inequality," *American Economic Review* 94, 426-454.

[9] Calvó-Armengol, A. and Y. Zenou (2004), "Social networks and crime decisions: The role of social structure in facilitating delinquent behavior," *International Economic Review* 45, 935-954.

[10] Case, A.C. and L.F. Katz (1991) "The company you keep: The effects of family and neighborhood on disadvantaged youths," NBER Working Paper No. 3705.

[11] Durlauf, S.E. (2004), "Neighborhood effects," in *Handbook of Regional and Urban Economics Vol. 4*, J.V. Henderson and J-F. Thisse (Eds.), Amsterdam: Elsevier Science, pp. 2173-2242.

[12] Epple, D. and R. Romano (1998), "Competition between public and private schools, vouchers and peer group effects," *American Economic Review* 88, 33-62.

[13] Evans, W.N, Oates, W.E and R.M. Schwab (1992), "Measuring peer group effects: A study of teenage behavior," *Journal of Political Economy* 100, 966-991.

[14] Freeman, L.C. (1978/79), "Centrality in social networks: Conceptual clarification," *Social Networks* 1, 215-239.

[15] Glaeser, E.L. Sacerdote, B., and J. Scheinkman (1996), "Crime and social interactions," *Quarterly Journal of Economics* 111, 508-548.

[16] Haynie, D.L. (2001), "Delinquent peers revisited: Does network structure matter?" *American Journal of Sociology* 106, 1013-1057.

[17] Ioannides, Y.M. and L. Datcher Loury (2004), "Job information networks, neighborhood effects, and inequality," *Journal of Economic Literature* 42, 1056-1093.

[18] Jackson, M. O. (2005), "A survey of models of network formation: Stability and efficiency," in *Group Formation in Economics: Networks, Clubs and Coalitions*, G. Demange and M. Wooders (Eds.), Cambridge: Cambridge University Press, pp. 11-57.

[19] Jackson, M.O. and B. Rogers (2004), "Search in the formation of large networks: How random are socially generated graphs?" Unpublished manuscript, California Institute of Technology.

[20] Moffitt, R.A. (2001), "Policy interventions, low-Level equilibria, and social interactions," in *Social Dynamics*, S.N. Durlauf and H.P. Young (Eds.), Cambridge: The MIT Press, pp. 45-82.

[21] Sacerdote, B. (2001), "Peer effects with random assignment: Results from Dartmouth roomates," *Quarterly Journal of Economics* 116, 681-704.

[22] Sah, R. (1991), "Social osmosis and patterns of crime," *Journal of Political Economy* 99, 1272-1295.

[23] Silverman, D. (2004), "Street crime and street culture," *International Economic Review* 45, 761-786.

[24] Sutherland, E.H. (1947), *Principles of Criminology*, fourth edition, Chicago: J.B. Lippincott.

[25] Topa, G. (2001), "Social interactions, local spillovers and unemployment," *Review of Economic Studies* 68, 261-295.

[26] Warr, M. (2002), *Companions in Crime: The Social Aspects of Criminal Conduct*, Cambridge: Cambridge University Press.

[27] Wasserman, S., and K. Faust (1994), *Social Network Analysis. Methods and Applications*, Cambridge: Cambridge University Press.

[28] Wooldridge, J.M. (2002), *Econometric Analysis of Cross Section and Panel Data*, Cambridge: The MIT Press.

Appendix 1: Description of control variables

Individual socio-demographic variables

female: dummy variable taking value one if the respondent is female.

race dummies: white, black or African American, 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 as1= D or lower, 2= C, 3=B, 4=A.

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 1as = 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 dummies: closest description of the job of (biological or non-biological) parent that is living with the child, coded as 6-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.

Global social interaction variables

friend attachment: dummy taking value one if the respondent reports that he/she feels that his/her friends cares very much about him/her

friend involvement: response to the question: "During the past week, how many times did you just hang out with friends", coded as 0= not at all, 1=1 or 2 times, 2=3 or 4 times, 3=5 or more times.

friend contacts: composite score of the values averaged on all nominated friends of the items derived from the questions: "Did you a) go to nominated friend (NF)'s house during the past seven days, b) meet NF after school to hang out or go somewhere during the past seven days, c) spend time with NF during the past weekend, d) talk to NF about a problem during the past seven days, e) talk to NF on the telephone during the past seven days, all coded as 1=yes, 0=no. (Crombach-alpha =0.84)

Local social interactions variables

strength of local interactions: composite score of the values averaged on direct friends only of the items listed in the description of friend contact. (Crombach-alpha =0.86).

quality of local interactions: average value across direct friends of mathematics score.

quality of local interactions (background): average value across direct friends of parent education.

protective factors of local interactions: composite scores of average value across direct friends of school attachment, parental care, friend attachment, social exclusion. (Crombach-alpha =0.72).

local average delinquency: average value across direct friends of delinquency index

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 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).

School variables

teachers quality: percentage of full-time classroom teachers holding Master's degree of higher.

school quality: ratio between full-time classroom teachers and average class size.

school type dummies: catholic or other private with religious affiliation, private with no religious affiliation, public (reference group), other.

students quality: number of students retained in the same grade for the next academic year (averaged on all grades and total amount of students held back if the school is ungraded).

strictness of school anti-crime regulations: composite score of the items derived from the questions: "In your school, what happens to a student who is caught: a) injuring another student, b) possessing alcohol, c) possessing an illegal drug, d) possessing a weapon, e) drinking alcohol at school, f) using an illegal drug at school, g) verbally abusing a teacher, h) physically injuring a teacher, i) stealing school property", coded as 1= no policy, verbal warning or minor actions, 2= in-school suspension (the student does not attend classes, but comes to school), 3= out-of-school suspension (the student must stay out of school for a time), 4= expulsion (the student must withdraw permanently). (Crombach-alpha 0.74).

TABLE 1: DESCRIPTIVE STATISTICS on the CRIME DATA SET (5,154 criminals; 116 networks)

	Mean	St.dev	Min	Max
female	0.23	0.30	0	1
age	14.82	1.69	10	19
health status	2.10	1.61	0	4
religion practice	1.51	0.71	0	4
black or African American	0.24	0.35	0	1
other races	0.05	0.06	0	1
school attendance	2.99	1.26	1	6
student grade	8.51	1.84	6	13
mathematics score	1.18	1.29	1	4
organized social participation	0.67	0.26	0	1
motivation in education:	1.87	0.77	1	4
relationship with teachers:	0.29	0.41	0	1
social exclusion:	3.37	1.72	1	5
school attachment	3.85	1.21	1	5
parental care	0.41	0.45	0	1
household size	4.52	1.16	1	6
two married parent family	0.30	0.35	0	1
single parent family	0.32	0.36	0	1
public assistance:	0.25	0.31	0	1
Mother working	0.54	0.44	0	1
parent education	3.19	1.66	1	5
parents age	42.31	7.81	33	75
parent occupation manager	0.09	0.11	0	1
parent occupation professional or technical	0.11	0.16	0	1
parent occupation office or sales worker	0.17	0.19	0	1
parent occupation manual	0.32	0.40	0	1
parent occupation military or security	0.06	0.07	0	1
parent occupation farm or fishery	0.01	0.02	0	1
parent occupation retired	0.04	0.08	0	1
parent occupation other	0.09	0.10	0	1
neighborhood quality	1.95	2.41	1	4
residential building quality	1.57	1.77	1	4
neighborhood safety	0.45	0.57	0	1
residential area type suburban	0.27	0.30	0	1
residential area type urban - residential only	0.10	0.12	0	1
residential area type 3 or more commercial properties - mostly retail	0.15	0.17	0	1
residential area type 3 or more commercial properties - mostly wholesale or industrial	0.20	0.28	0	1
residential area type other	0.18	0.23	0	1
friend attachment:	0.45	0.47	0	1
friend involvement:	2.40	1.10	0	3
friend contacts	0.88	0.10	0	1
physical development	3.06	2.34	1	5
self esteem	3.81	1.18	1	6
school catholic or other private, religious affiliation	0.09	0.17	0	1
school private, no religious affiliation	0.02	0.14	0	1
school quality	2.25	3.32	0.7	4.78
students quality	491.13	205.01	142.43	856.64
teachers quality	49.29	24.41	0	100
strictness of school anti-crime regulations	2.11	1.75	1	4

TABLE 2: DESCRIPTIVE STATISTICS on the EDUCATION DATA SET (11,964 pupils; 199 networks)

	Mean	St.dev	Min	Max
female	0.41	0.35	0	1
age	15.29	1.85	10	19
health status	3.01	1.77	0	4
religion practice	2.71	0.77	0	4
black or African American	0.20	0.31	0	1
other races	0.12	0.15	0	1
school attendance	3.28	1.86	1	6
student grade	9.27	3.11	6	13
delinquency index	0.52	2.25	0	3
mathematics score	1,99	1,33	1	4
organized social participation	0.62	0.22	0	1
motivation in education:	2.23	0.88	1	4
relationship with teachers:	0.12	0.34	0	1
social exclusion:	2.26	1.81	1	5
school attachment	2.59	1.76	1	5
parental care	0.69	0.34	0	1
household size	3.52	1.71	1	6
two married parent family	0.41	0.57	0	1
single parent family	0.23	0.44	0	1
public assistance:	0.12	0.16	0	1
mother working	0.65	0.47	0	1
parent education	3.69	2.06	1	5
parents age	40.12	13.88	33	75
parent occupation manager	0.11	0.13	0	1
parent occupation professional or technical	0.09	0.21	0	1
parent occupation office or sales worker	0.26	0.29	0	1
parent occupation manual	0.21	0.32	0	1
parent occupation military or security	0.09	0.12	0	1
parent occupation farm or fishery	0.04	0.09	0	1
parent occupation retired	0.06	0.09	0	1
parent occupation other	0.11	0.16	0	1
neighborhood quality	2.99	2.02	1	4
residential building quality	2.95	1.85	1	4
neighborhood safety	0.51	0.57	0	1
residential area type suburban	0.32	0.38	0	1
residential area type urban - residential only	0.18	0.21	0	1
residential area type 3 or more commercial properties - mostly retail	0.12	0.15	0	1
residential area type 3 or more commercial properties - mostly wholesale or industrial	0.13	0.18	0	1
residential area type other	0.19	0.25	0	1
friend attachment:	0.49	0.54	0	1
friend involvement:	1.88	1.56	0	3
friend contacts	0.89	0.12	0	1
physical development	3.14	2.55	1	5
self esteem	3.93	1.33	1	6
school catholic or other private. religious affiliation	0.19	0.24	0	1
school private. no religious affiliation	0.14	0.19	0	1
school quality	2.45	3.53	0.5	4.89
students quality	412.77	240.78	140.32	864.12
teachers quality	54.12	26.53	0	100
strictness of school anti-crime regulations	2.21	1.89	1	4

TABLE 3: MODEL (7) ESTIMATION RESULTS

	dep. var. Delinquency index	**dep. var. School performance index**
Bonacich measure	0.3765** (0.1130)	0.2808*** (0.0929)
female	-0.1322**(0.0623)	0.0911**(0.0404)
age	0.0723 (0.1091)	0.0224 (0.0665)
health status	0.0912 (0.2121)	-0.1055 (0.1919)
religion practice	-0.1402***(0.0165)	0.0751 (0.0645)
black or African American	0.1005 (0.0884)	-0.0792* (0.0522)
other races	0.0155 (0.0505)	0.1450*** (0.0323)
school attendance	0.1193 (0.2020)	0.0791 (0.1011)
student grade	-0.0374 (0.0466)	0.0866*** (0.0222)
mathematics score	-0.1655***(0.0043)	0.1889**(0.0886)
delinquency index	-	-0.2922***(0.0624)
organized social participation	0.0048 (0.1239)	0.0911** (0.0067)
motivation in education:	-0.3422***(0.0012)	0.8825***(0.1002)
household size	0.0021 (0.0019)	-0.0011 (0.0018)
two married parent family	-0.4439***(0.0045)	0.4350 (0.2255)
single parent family	0.2554 (0.1704)	-0.5224*** (0.2027)
public assistance:	0.8625***(0.1558)	-0.3122* (0. 0.2028)
mother working	0.0073 (0.1901)	0.1575 (0.1413)
parent education	-0.1100** (0.0523)	0.3207*** (0.0779)
parents age	0.0002 (0.1442)	0.0005 (0.1350)
parent occupation manager	-0.0222 (0.4332)	-0.0105 (0.2683)
parent occupation professional or technical	-0.0303 (0.5215)	-0.0134 (0.2750)
parent occupation office or sales worker	0.0101 (0.1312)	0.0089 (0.1623)
parent occupation manual	0.0961 (0.0808)	-0.0999** (0.0471)
parent occupation military or security	-0.0552 (0.2291)	0.0117 (0.1298)
parent occupation farm or fishery	0.0202 (0.4051)	-0.0779 (0.4015)
parent occupation retired	0.0095 (0.2265)	0.1633 (0.1772)
parent occupation other	0.0299 (0.2040)	0.0125 (0.3041)
relationship with teachers	0.2710 (0.2752)	-0.6723*** (0.2258)
social exclusion:	0.0566 (0.4561)	-0.4559** (0.2053)
school attachment	0.0409**(0.0206)	-0.1975**(0.0982)
parental care	-0.2699***(0.0219)	0.7142***(0.0915)
neighborhood quality	-0.0521 (0.3747)	0.0066 (0.1140)
residential building quality	-0.1052**(0.0531)	0.1925***(0.0678)
neighborhood safety	1.0084***(0.4101)	0.7228 (0.7940)
residential area type suburban	0.1111 (0.5643)	-0.0451 (0.2186)
residential area type urban - residential only	-0.0445 (0.4499)	0.2730*** (0.0333)
residential area type 3 or more commercial properties - mostly retail	0.0455 (0.6551)	0.0052 (0.3055)
residential area type 3 or more commercial properties - mostly wholesale or industrial	0.0912 (0.7806)	-0.0594 (0.3108)
residential area type other	-0.0065 (0.4120)	0.0085 (0.0955)
school catholic or other private. religious affiliation	-0.0399 (0.0388)	0.3431*** (0.0102)
school private. no religious affiliation	-0.0355 (0.0299)	0.3021(0.3553)
school quality	-0.0707 (0.0775)	-0.1655** (0.0834)
students quality	-0.0020 (0.0256)	0.0062 (0.1220)
teachers quality	-0.0165 (0.0211)	0.0350*** (0.0009)
strictness of school anti-crime regulations	-0.3903 (0.3954)	0.1290** (0.0608)
friend attachment:	-0.1656** (0.0832)	-0.0019 (0.1211)
friend involvement:	0.1224** (0.0556)	-0.2231** (0.0991)
friend contacts	0.6441 (0.5974)	0.6905 (0.5997)
strength of local interactions	0.6505**(0.3252)	0.1293**(0.0585)
quality of local interactions	-0.1505** (0.0681)	0.1267*** (0.0105)

quality of local interactions (family background)	-0.0888* (0.0592)	0.1944** (0.0849)
protective factors of local interactions	-0.1284***(0.0239)	0.0682 (0.0877)
physical development	0.1111 ** (0.0558)	0.1520 (0.2107)
self esteem	0.2019 ***(0.0535)	0.0716***(0.0281)
School dummies	Yes	yes
R^2	.5315	.5464

Notes: White-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.
Number of observations column two: 597,864 (5,154 criminals; 116 networks).
Number of observations column three: 2,380,836 (11,964 pupils; 199 networks).

TABLE 4: MODEL (7) ESTIMATION RESULTS

	dep.var. Delinquency index	**dep.var. School Performance index**
betweeness measure	0.3998**(0.1781)	0.3585** (0.1697
female	-0.1325** (0.0701)	0.0948**(0.429)
age	0.1100 (0.1122)	0.0479 (0.0598)
health status	0.1799 (0.2654)	-0.0788 (0.1133)
religion practice	-0.2152*** (0.0122)	0.0651 (0.0512)
black or African American	0.1218 (0.1031)	-0.0954* (0.0345)
other races	0.0577 (0.0565)	0.1569*** (0.0571)
school attendance	0.1923 (0.2131)	0.1007 (0.1011)
student grade	-0.0478**(0.0222)	0.0680*** (0.0100)
mathematics score	-0.2215*** (0.0156)	0.2555*** (0.0555)
delinquency index	-	-0.4909***(0.1055)
organized social participation	*0.0131 (0.0081)	0.0110** (0.0052)
motivation in education:	-0.4076***(0.0055)	0.8112***(0.0666)
household size	0.0020** (0.0009)	-0.0013 (0.0099)
two married parent family	-0.4575***(0.0023)	0.5065 (0.4595)
single parent family	0.3811**(0.1432)	-0.5469***(0.1454)
public assistance:	0.7990***(0.1991)	-0.2992* (0.1899)
mother working	0.0101 (0.1563)	0.1510 (0.1155)
parent education	-0.1640***(0.0091)	0.3101*** (0.0654)
parents age	0.0009 (0.1288)	0.0007 (0.1445)
parent occupation manager	-0.0344 (0.4278)	-0.0129 (0.2428)
parent occupation professional or technical	-0.0324 (0.5321)	-0.0055 (0.2650)
parent occupation office or sales worker	0.0099 (0.1657)	0.0127 (0.2861)
parent occupation manual	0.1010**(0.0459)	-0.0095** (0.0043)
parent occupation military or security	-0.0189 (0.1787)	0.0421 (0.1342)
parent occupation farm or fishery	0.0332 (0.4041)	-0.0991 (0.4143)
parent occupation retired	0.0256 (0.2516)	0.1431 (0.1321)
parent occupation other	0.0239 (0.2114)	0.0254 (0.3244)
relationship with teachers:	0.3031 (0.2042)	-0.7439***(0.2955)
social exclusion:	0.0499 (0.1399)	-0.3949** (0.1881)
school attachment	0.10779***(0.0299)	-0.1865**(0.0875)
parental care	-0.2974***(0.0169)	0.6947***(0.1099)
neighborhood quality	-0.0542 (0.4255)	0.0094 (0.1143)
residential building quality	-0.0876** (0.0394)	0.1912***(0.0710)
neighborhood safety	1.0220***(0.4005)	0.7859 (0.7439)
residential area type suburban	0.1237 (0.5695)	-0.0121 (0.1908)
residential area type urban - residential only	-0.0541 (0.4578)	0.3105*** (0.0334)
residential area type 3 or more commercial properties - mostly retail	0.0652 (0.6655)	0.0044 (0.3615)
residential area type 3 or more commercial properties - mostly wholesale or industrial	0.0783 (0.7592)	-0.0915 (0.2778)
residential area type other	-0.0053 (0.4885)	0.0095 (0.0514)
school catholic or other private. religious affiliation	-0.0541***(0.0045)	0.3431*** (0.0231)
school private. no religious affiliation	-0.0129***(0.0077)	0.3454 (0.3431)
school quality	-0.0678(0.0679)	-0.1651** (0.0743)
students quality	-0.0010 (0.0263)	0.0029 (0.1066)
teachers quality	-0.0198 (0.0158)	0.0606*** (0.0021)
strictness of school anti-crime	0.4312**(0.2043)	0.1293** (0.0601)

regulations		
friend attachment:	-0.1699**(0.0764)	-0.0010 (0.0998)
friend involvement:	0.1354**(0.0609)	-0.2231** (0.1103)
friend contacts	0.4956 (0.3998)	0.6504 (0.5971)
strength of local interactions	0.6627**(0.3030)	0.1349**(0.0607)
quality of local interactions	-0.1349** (0.0679)	0.1265*** (0.0065)
quality of local interactions (background)	-0.1475** (0.0705)	0.1430** (0.0644)
protective factors of local interactions	-0.0911**(0.0414)	0.0778 (0.0788)
physical development	0.1399*** (0.0505)	0.1702 (0.1575)
self esteem	0.2123***(0.0547)	0.1430***(0.0342)
School dummies	yes	yes
R^2	.5116	.4777

Notes: White-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.
Number of observations column two: 597,864 (5,154 criminals; 116 networks).
Number of observations column three: 2,380,836 (11,964 pupils; 199 networks).