Juvenile Delinquency and Conformism

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This article studies whether conformism behavior affects individual outcomes in crime. We present a social network model of peer effects with ex ante heterogeneous agents and show how conformism and deterrence affect criminal activities. We then bring the model to the data by using a very detailed data set of adolescent friendship networks. A novel social network–based empirical strategy allows us to identify peer effects for different types of crimes. We find that conformity plays an important role for all crimes, especially for petty crimes. This suggests that, for juvenile crime, an effective policy should be measured not only by the possible crime reduction it implies but also by the group interactions it engenders. (*JEL* A14, C21, D85, K42, Z13)

1. Introduction

A large literature has developed on the general causes of, and the impact of public policy on, crime. Yet, no consensus has emerged on quite basic issues, such as, for example, the effects of incentives, both positive and negative, on crime.

Juvenile crime is an important aspect of this debate. According to the US Department of Justice, juveniles were involved in 16% of all violent arrests and 32% of all property crime arrests in 1999. In addition, more than 100,000 juveniles are held in residential placement on any given day in the United

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States. However, despite these figures, there are still many unanswered questions about juvenile crime. Some have shown that deterrence has a negative impact on juvenile crime (Levitt 1998; Mocan and Rees 2005). It has also been shown that crime committed by younger people have higher degrees of social interactions (Glaeser et al. 1996; Jacob and Lefgren 2003; Patacchini and Zenou 2008).[1]

There is indeed a growing literature in economics suggesting that peer effects are very strong in criminal decisions. Case and Katz (1991), using data from the 1989 National Bureau of Economic Research survey of youths living in low-income Boston neighborhoods, find that the behaviors of neighborhood peers appear to substantially affect criminal activities of youth behaviors. They find that the direct effect of moving a youth with given family and personal characteristics to a neighborhood where 10% more of the youths are involved in crime than in his/her initial neighborhood is to raise the probability that the youth will become involved in crime by 2.3%. Ludwig et al. (2001) and Kling et al. (2005) explore this last result by using data from the moving to opportunity (MTO) experiment that relocates families from high- to low-poverty neighborhoods. They find that this policy reduces juvenile arrests for violent offences by 30%–50% as compared to the control group. This also suggests very strong social interactions in crime behaviors. Patacchini and Zenou (2008) test the role of weak ties[2] in explaining criminal activities, revealing that weak ties have a statistically significant and positive effect both on the probability to commit crime and on its level. Finally, Bayer et al. (2009) consider the influence that juvenile offenders serving time in the same correctional facility have on each other's subsequent criminal behavior. They find strong evidence of peer effects in criminal activities since exposure to peers with a history of committing a particular crime increases the probability that an individual who has already committed the same type of crime recidivates with that crime.

The aim of the present article is to analyze the role of conformism in juvenile crime using a network perspective. There are two important challenges in the empirics of social interactions: (a) the assessment of the *existence* of the endogenous effect of peers and (b) the explanation of *how* peers influence each other, that is, the mechanism generating such social interactions.[3]

We first present a social network model where individual utility depends on conformism. Conformism is the idea that the easiest and hence best life is attained by doing one's very best to blend in with one's surroundings and to do nothing eccentric or out of the ordinary in any way. It may well be

1. In the crime literature, the positive correlation between self-reported delinquency and the number of delinquent friends reported by adolescents has proven to be among the strongest and one of the most consistently reported findings (see, e.g., Warr 1996, 2002; Matsueda and Anderson 1998; Haynie 2001).

2. Weak ties are defined in terms of lack of overlap in personal networks between any two agents; that is, weak ties refer to a network of acquaintances who are less likely to be socially involved with one another (see, in particular, Granovetter 1973).

3. See, in particular, the special issue on peer effects in the *Journal of Applied Econometrics* (Durlauf and Moffitt 2003).

best expressed in the old saying, "When in Rome, do as the Romans do." To be more specific, using an explicit network analysis,[4] we develop a model where conformism[5] associated with deterrence is the key determinant of criminal activities. Our model is as follows. Each criminal belongs to a group of best friends and derives utility from exerting crime effort. We have a standard costs/benefits structure a la Becker with an added element, conformism. The new aspect of this model is that the social norm is endogenous and depends on the structure of the network. Indeed, direct friends define a social norm, and depending of the location in the network, each individual has a different reference group. The utility function is such that each individual wants to minimize the social distance between his/her crime level and that of his/her reference group.

We derive the Nash equilibrium of this game and obtain that, when individuals are ex ante heterogenous (e.g., different race, sex, parents' education, etc.), they provide effort proportional to that of their reference group of best friends and that deterrence reduces crime.[6] An interesting result is that, when individuals are ex ante identical, that is, differ only by their location in the network, then, in equilibrium, all agents provide the same effort level. In other words, the Bonacich centrality index[7] is the same for all individuals in the network. This is a surprising result since Ballester et al. (2006), using a similar social network model but without conformism, find that, when individuals are ex ante identical, each of them will provide a different effort level depending on his/her location in the network (as measured by his/her Bonacich index). Our result is due to the fact that the cost of deviating from the norm is sufficiently high so that individuals behave identically in equilibrium. However, when an additional heterogeneity is introduced (apart from the location of the network, individuals are heterogenous in their ability of committing crime, which is correlated with their *idiosyncratic characteristics*),

4. There is a growing literature on networks in economics. See the recent literature surveys by Goyal (2007) and Jackson (2007, 2008).

5. In economics, different aspects of conformism and social norms have been explored from a theoretical point of view. To name a few, (a) peer pressures and partnerships (Kandel and Lazear 1992) where peer pressure arises when individuals deviate from a well-established group norm, for example, individuals are penalized for working less than the group norm, (b) religion (Iannaccone 1992; Berman 2000) since praying is much more satisfying the more average participants there are, and (c) social status and social distance (Akerlof 1980, 1997; Bernheim 1994; Battu et al. 2007, among others) where deviations from the social norm (average action) imply a loss of reputation and status.

6. In this model, we assume that benefits of crime always outweigh the costs. In the case of ex ante heterogeneities, one could have a two-stage game, where in the first stage, people decide to become criminal or not and then, in the second stage, only those who decide to be criminal (i.e., all individuals for which the benefits of crime are lower than the costs) will be embedded in a network. This will not affect the main results since we will work on a subset of people who are criminals. This is because, in our utility function, only criminals affect other criminals, which means that for noncriminals, the social network does not play any role.

7. To be more precise, the Bonacich centrality measure takes into account both direct and indirect friends of each individual but puts less weight to distant friends.

individuals deviate from the social norm and behave partly according to their ability.

This theoretical model is along the lines of the growing literature on the social aspects of crime. In Sah (1991), the social setting affects the individual perception of the costs of crime and is thus conducive to a higher or a lower sense of impunity. In Glaeser et al. (1996), criminal interconnections act as a social multiplier on aggregate crime. Calvó-Armengol and Zenou (2004) and Ballester et al. (2006, 2010) develop social network models of pure peer effects and no conformism.[8,9]

We then test our model using the US National Longitudinal Survey of Adolescent Health (AddHealth), which contains unique detailed information on friendship relationships among delinquent teenagers. Empirical tests of models of social interactions are quite problematic because of well-known issues that render the identification and measurement of peer effects quite difficult: (a) reflection, which is a particular case of simultaneity (Manski 1993), and (b) endogeneity, which may arise for both peer self-selection and unobserved common (group) correlated effects.

In this article, we exploit the architecture of social networks to overcome this set of problems and to achieve the identification of endogenous peer effects. More specifically, in social networks, each agent has a different peer group, that is, different friends with whom each teenager directly interacts. This feature of social networks guarantees the presence of excluded friends from the reference group (peer group) of each agent, which are however included in the reference group of his/her best (direct) friends. This identification strategy is similar in spirit to the one used in the standard simultaneous equation model, where at least one exogenous variable needs to be excluded from each equation. In addition, because we observe individuals over networks, we can use a specification of the empirical model with a network-specific component. By doing so, we are able to control for the presence of network-specific unobserved factors affecting both individual and peer behaviors. Such factors might be important omitted variables driving the sorting of agents into networks or effects arising from unobservable shocks that affect the network as a whole. Such an approach proves also useful to tackle one further empirical concern stemming from the fact that each agent's peer group (rather than the whole network) might be affected by common unobservable factors. Indeed, once our particularly large information on individual (observed) variables and network characteristics are taken into account, (within-network) linking decisions appear uncorrelated with peer group–level observables. Finally, the variety of questions in the AddHealth questionnaire allows us to find observable

8. The difference between our present model and these three models are discussed in detail at the end of Section 2.2 below.

9. Linking social interactions with crime has also been done in dynamic general equilibrium models (İmrohoroğlu et al. 2000; Lochner 2004) and in search-theoretic frameworks (Burdett et al. 2003, 2004; Huang et al. 2004). Other related contributions on the social aspects of crime include Silverman (2004), Verdier and Zenou (2004), Calvó-Armengol et al. (2007), and Ferrer (2010).

proxies for typically unobserved individual characteristics that are commonly believed to induce self-selection (ability, leadership propensity, parental care, etc.). The addition of "school dummies" is used to control for school-specific inputs.

Observe that school dummies also account for differences in the strictness of anticrime regulations across schools as well as for local crime policies. The identification of deterrence effects on crime is a difficult empirical exercise because of the well-known potential simultaneity and reverse causality issues (Levitt 1997), which cannot totally be solved using our network-based approach. We avoid to directly estimate such effects (i.e., to include in the model specification observable measures of deterrence, such as local police expenditures or the arrest rate in the local area). Rather, we focus our attention on the estimation of peer effects on crime, once deterrence effects have been controlled for.

This strategy leads to the following main findings: Conformity plays an important role in explaining criminal behavior of adolescents, especially for petty crimes. Specifically, a one standard deviation (SD) increase in individual i's taste for conformity or equivalently in the average criminal activity of individual i's reference group raises individual i's level of crime by about 5.2% of a SD when total crime is considered. It ranges from 9.8 to 1.4 moving from petty crimes to more serious crimes.

The analysis of peer effects is, however, a complex issue, and our analysis has obviously some limitations. First, our model is only one of the possible mechanisms generating such externalities. It is not, however, rejected by our data and highlight the importance of network topology in explaining criminal activities. Second, in the absence of experimental data, one can never be sure to have captured all the behavioral intricacies that lead individuals to associate with others. Nevertheless, by using both within- and between-network variations and by taking advantage of the unusually large information on teenagers' behavior provided by our data set, our analysis is one of the best attempts to overcome the empirical difficulties.

The rest of the article can be described as followed. In Section 2, we derive our main theoretical results. Section 3 describes the data and the empirical strategy. In Section 4, we present our empirical results, both for all crimes and for each type of crime. Section 5 checks the sensitivity of our results when the actual directions of the friendship nominations are exploited. Finally, Section 6 concludes.

2. Theory

2.1 The Basic Model

There are N individuals/criminals in the economy.

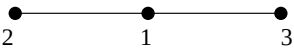
2.1.1 The Network.

$N = \{1, \ldots, n\}$ is a finite set of agents. The n-square adjacency matrix $\mathbf{G}$ of a network $\mathbf{g}$ keeps track of the direct connections in this network. Here, two players i and j are directly connected (i.e., best friends) in

g if and only if $g_{ij} = 1$, and $g_{ij} = 0$, otherwise. Given that friendship is a reciprocal relationship, we set $g_{ij} = g_{ji}$.[10] We also set $g_{ii} = 0$. The set of individual i's best friends (direct connections) is $N_i(\mathbf{g}) = \{j \neq i \mid g_{ij} = 1\}$, which is of size g_i $\left(\text{i.e., } g_i = \sum_{j=1}^{n} g_{ij} \text{ is the number of direct links of individual } i\right)$. This means in particular that, if i and j are best friends, then in general $N_i(\mathbf{g}) \neq N_j(\mathbf{g})$ unless the graph/network is complete (i.e., each individual is friend with everybody in the network). This also implies that groups of friends may overlap if individuals have common best friends. To summarize, the *reference group* of each individual i is $N_i(\mathbf{g})$, that is, the set of his/her best friends, which does not include himself/herself.

Let $\gamma_{ij} = g_{ij}/g_i$, for $i \neq j$, and set $\gamma_{ii} = 0$. By construction, $0 \leqslant \gamma_{ij} \leqslant 1$. Note that $\boldsymbol{\gamma}$ is a row normalization of the initial friendship network **g**, as illustrated in the following example, where **G** and $\boldsymbol{\Gamma}$ are the adjacency matrices of, respectively, **g** and $\boldsymbol{\gamma}$.

Example 1. Consider the following friendship network **g**:



Then,

$$\mathbf{G} = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix} \quad \text{and} \quad \boldsymbol{\Gamma} = \begin{bmatrix} 0 & 1/2 & 1/2 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}.$$

2.1.2 Preferences. We focus on adolescent crime and we denote by $e_i(\mathbf{g})$ the crime effort level of criminal i in network **g**. We also denote by $\bar{e}_i(\mathbf{g})$ the average crime effort of the g_i best friends of i, which is given by

$$\bar{e}_i(\mathbf{g}) = \frac{1}{g_i} \sum_{j=1}^{j=n} g_{ij} e_j. \tag{1}$$

From now on, when there is no risk of confusion, we drop the argument **g**. Each individual/criminal selects an effort $e_i \geqslant 0$ and obtains a payoff $u(e_i, \bar{e}_i)$ given by the following utility function:[11]

$$u_i(e_i, \bar{e}_i) = a + b_i e_i - p e_i f - c e_i^2 - d(e_i - \bar{e}_i)^2 \tag{2}$$

with $a, c, d > 0$ and $b_i > 0$ for all i.

10. This is not an important assumption since all our theoretical results hold even when $g_{ij} \neq g_{ji}$. We discuss this issue in Section 5.

11. Crime effort e_i could mean different things, but here e_i is the frequency of crime rather than actually taking the time to plan and not get caught. This is why the assumption that the probability of being caught is increasing with effort makes sense in the utility function.

This utility has a standard cost/benefit structure (as in Becker 1968). The proceeds from crime are given by $a + b_i e_i$ and are increasing in own effort e_i. There is an ex ante *idiosyncratic heterogeneity*, b_i, which captures the fact that individuals differ in their ability (or productivity) of committing crime. Indeed, for a given effort level e_i, the higher b_i, the higher the productivity and thus the higher the booty $a + b_i e_i$. Observe that b_i is assumed to be deterministic, perfectly *observable* by all individuals in the network and corresponds to the observable characteristics of individual i (like, e.g., sex, race, age, parental education, etc.) and to the observable average characteristics of individual i's best friends, that is, average level of parental education of i's friends, etc. (contextual effects). To be more precise, b_i can be written as

$$b_i(\mathbf{x}) = \sum_{m=1}^{M} \beta_m x_i^m + \frac{1}{g_i} \sum_{m=1}^{M} \sum_{j=1}^{n} \theta_m g_{ij} x_j^m, \tag{3}$$

where x_i^m is a set of M variables accounting for observable differences in individual, neighborhood, and school characteristics of individual i and β_m, θ_m are parameters. This form is only adopted for the ease of the empirical implementation.

The costs of committing crime are captured by the probability to be caught pe_i, which increases with own effort e_i, as the apprehension probability increases with one's involvement in crime, times the fine f, that is, the severity of the punishment. Also, as it is now quite standard (see, e.g., Verdier and Zenou 2004; Conley and Wang 2006), individuals have a *moral* cost of committing crime equal to ce_i^2, which is reflected here by their degree of honesty c.[12] So the higher c, the higher the moral cost and it increases with crime effort.

Finally, the new element in this utility function is the last term $d(e_i - \bar{e}_i)^2$, which reflects the influence of friends' behavior on own action. It is such that each individual wants to minimize the social distance between himself/herself and his/her reference group, where d is the parameter describing the taste for conformity. Indeed, the individual loses utility $d(e_i - \bar{e}_i)^2$ from failing to conform to others. This is the standard way economists have been modeling conformity (see, among others, Akerlof 1980, 1997, Bernheim 1994, Kandel and Lazear 1992; Fershtman and Weiss 1998). We can analyze the bilateral influences of this utility function. They are given by

$$\frac{\partial^2 u_i(e_i, \bar{e}_i)}{\partial e_i \partial e_j} = \begin{cases} -2(c+d) < 0 & \text{when } i = j; \\ 0 & \text{when } i \neq j \text{ and } g_{ij} = 0; \\ 2d > 0 & \text{when } i \neq j \text{ and } g_{ij} = 1. \end{cases}$$

12. Assuming different degrees of honesty c_i would not change any of our results.

Since, when $i \neq j$, $2d > 0$, an increase in effort from j triggers an upward shift in i's response and thus efforts are *strategic complements* from i's perspective within the pair (i, j).

Observe that beyond the idiosyncratic heterogeneity, b_i, there is a second type of heterogeneity, referred to as *peer heterogeneity*, which captures the differences between individuals due to network effects. Here, it means that individuals have different types of friends and thus different reference groups $\bar{e}_i$. As a result, the social norm each individual i faces is endogenous and depends on his/her location in the network as well as the structure of the network. Indeed, in a star-shaped network (as the one described in Figure 1) where each individual is at most distance 2 from each other, the value of the social norm will be very different than a circle network, where the distance between individuals can be very large.

2.2 A Simple Symmetric Case

In this section, we assume that, ex ante, all individuals/criminals are identical, that is, same ex ante idiosyncratic heterogeneity, so that $b_i = b$.[13] This of course does not mean that they have the same peer heterogeneity since individuals have different reference groups. We can calculate the Nash equilibrium of this game where each individual chooses e_i by taking as given the actions of the other players. We have the following result.

Proposition 1. Assume that $b_i = b$ and $b > pf$. Then the conformity game with payoffs given by (equation 2) has a unique Nash equilibrium in pure strategies, which is equal to

$$e_i^* = \bar{e}_i^* = \frac{b - pf}{2c}. \tag{4}$$

In particular, the higher the deterrence, the lower the crime level.

Proof. See Appendix A. □

This is an interesting result. It says that, even if individuals are ex ante heterogeneous because of their location in the network and thus have different reference groups and social norms (peer heterogeneity), in a conformist equilibrium where each individual would like to conform as much as possible to the norm of his/her reference group, all individuals will exert the same effort level. The equilibrium effort e_i^* is increasing in the booty b, decreasing in the deterrence pf and in the disutility of committing crime c. In other words, ex ante heterogeneity and the distribution (in particular the variance) of population do not matter in a conformist equilibrium even if it does ex ante. It is really the average that plays a crucial role in this model. This contrasts with the results

13. We relax these assumptions in Section 2.3.

of Ballester et al. (2006)[14] who find that, when the utility function has not this conformism component, ex ante heterogenous agents are ex post heterogenous in terms of outcomes.

Let us explain in more detail why in this model the location in the network does not matter for equilibrium effort, whereas it does in Ballester et al. (2006).

The model of Ballester et al. (2006) is the so-called *local aggregate* model where peer (social network) effects enter in the utility function as follows:

$$u_i(e_i, g) = \underbrace{a + b_i e_i - p e_i f - c e_i^2}_{\text{own concavity}} + \underbrace{d \sum_{j=1}^{n} g_{ij} e_i e_j}_{\text{local aggregate peer effects}} . \quad (5)$$

It is thus the *sum of the efforts of his/her peers*, that is, $\sum_{j=1}^{n} g_{ij} e_i e_j$, that affects the utility of individual *i*. So the more delinquent *i* has criminal friends and the more active they are, the higher is his/her utility. On the contrary, in the so-called *local average* model (our model), the utility function is given by equation (2). In that case, it is the deviation from the *average of the efforts of his/her peers* that affects the utility of individual *i*. So the closer is *i*'s effort from the average of his/her friends' efforts, the higher is his/her utility.

Consequently, the two models are quite different. From a pure technical point of view, the adjacency matrix $\mathbf{G}$ of direct links of the initial network totally characterizes the peer effects in the *local aggregate* model, whereas it is a transformation of this matrix $\mathbf{G}$ to a weighted stochastic matrix $\mathbf{\Gamma}$ that characterizes the peer effects in the *local average* model.

Given these two aspects, the result of Proposition 1 is not that surprising. Indeed, in both models, it has been shown that the Nash equilibrium effort of each individual is proportional to his/her (Bonacich) centrality in the network (Ballester et al. 2006). In the local aggregate model, even if individuals are ex ante identical (i.e., same own concavity), their position in the network is different, which means that their (Bonacich) centrality is also different. Since the latter is basically characterized by the matrix $\mathbf{G}$,[15] then each individual will exert a different effort since he/she has a different position in the network. On the contrary, in the local average model, if individuals are ex ante identical and even if their position in the network is different, their (Bonacich) centrality will be the same because it is defined by the matrix

14. And also Calvó-Armengol and Zenou (2004) and Ballester et al. (2010).

15. To be more precise, the vector of Bonacich centralities in the local aggregate model $\boldsymbol{\eta}^{\text{lag}}(\phi, \mathbf{g})$ is given by

$$\boldsymbol{\eta}^{\text{lag}}(\phi, \mathbf{g}) = \sum_{k=0}^{+\infty} \phi^k \mathbf{G}^k \mathbf{1},$$

where $\mathbf{1}$ is a vector of one.

$\mathbf{\Gamma}$ and not by $\mathbf{G}$, where $\mathbf{\Gamma}$ is a row normalization matrix of $\mathbf{G}$.[16] From an economic viewpoint, in the local aggregate model, different positions in the network imply different effort levels because it is the sum of efforts that matter, whereas in the local average model, the position in the network does not matter since it is the deviation from the average effort of friends that affects the utility.

Take, for example, the star-shaped network with three individuals in Example 1. In the local *aggregate* model, individual 1 will exert the highest effort since he/she has two direct friends and will thus receive high local complementarities, given by e_2+e_3, whereas the two other individuals has only one friend and each will only receive e_1. In the local average model, this is not anymore true since the peer effect component of individual 1 is $-\left[e_1-\left(\frac{e_2+e_3}{2}\right)\right]^2$, whereas for individuals 2 and 3, we have $-\left(e_2-\frac{e_1}{2}\right)^2$ and $-\left(e_3-\frac{e_1}{2}\right)^2$, respectively. The differences in the direct links are already small, and, in equilibrium, where both direct and indirect links are taken into account (through the Bonacich centralities), these peer effect aspects turn out to be the same for all individuals in the network.

2.3 The General Model

Let us generalize this theoretical model for the case of ex ante heterogenous individuals in terms of b_i. We have the following result.

Proposition 2. Consider the general case when all individuals have ex ante idiosyncratic and peer heterogeneities and different tastes for conformity. Assume that $b_i > pf$ for all i. Then there exists a unique Nash equilibrium where each individual i provides the following crime effort:

$$e_i^* = \frac{d}{c+d}\bar{e}_i + \frac{b_i}{2(c+d)} - \frac{pf}{2(c+d)}$$

$$= \left(\frac{d}{c+d}\right)\frac{1}{g_i}\sum_{j=1}^{j=n} g_{ij}e_j + \frac{b_i}{2(c+d)} - \frac{pf}{2(c+d)}, \tag{6}$$

which is increasing with the average crime effort of the reference group $\bar{e}_i$,

$$\frac{\partial e_i^*}{\partial \bar{e}_i} > 0. \tag{7}$$

16. To be more precise, the vector of Bonacich centralities in the local average model $\boldsymbol{\eta}^{\text{lav}}(\phi,\boldsymbol{\gamma})$ is given by

$$\boldsymbol{\eta}^{\text{lav}}(\phi,\boldsymbol{\gamma}) = \sum_{k=0}^{+\infty}\phi^k\mathbf{\Gamma}^k\mathbf{1}$$

$$= \frac{1}{1-\phi}\mathbf{1},$$

where the second equality is shown in the proof of Proposition 1 in Appendix A.

Furthermore, for a given $\bar{e}_i$, this equilibrium crime effort e_i^* is increasing with ex ante heterogeneity b_i and decreasing with deterrence pf,

$$\frac{\partial e_i^*}{\partial b_i} > 0 \quad \text{and} \quad \frac{\partial e_i^*}{\partial pf} < 0, \tag{8}$$

whereas its relationship with the taste for conformity d is ambiguous since

$$\frac{\partial e_i^*}{\partial d} \gtreqless 0 \Leftrightarrow \bar{e}_i \gtreqless \frac{b_i - pf}{2c}. \tag{9}$$

Proof. See Appendix A.

The previous result of Proposition 1 does not hold anymore since there are now both *idiosyncratic* and *peer heterogeneities*. We find that individuals will provide criminal effort proportional to their reference group $\bar{e}_i$ (see equation (7)) and to their ex ante idiosyncratic heterogeneity b_i (see equation (8)). Also, deterrence pf will negatively affect the crime effort (see equation (8)). Thus, not surprisingly, Proposition 2 shows that the only Nash equilibrium is asymmetric since each individual provides different crime efforts. Furthermore, the effect of the taste for conformity d on equilibrium crime effort e_i^* is ambiguous because there are two opposite effects. On the one hand, higher d increases e_i^* because of higher peer effects. On the other, higher d decreases e_i^* because of a higher chance to be caught. As a result, as can been seen in equation (9), if the first effect dominates the second one, then the relationship between d and e_i^* is positive.

3. Data and Empirical Strategy

3.1 Data

Our data source is the National Longitudinal Survey of Adolescent Health (AddHealth), which contains detailed information on a nationally representative sample of 90,118 students in roughly 130 private and public schools, entering grades 7–12 in the 1994–1995 school year.[17] AddHealth contains unique information on friendship relationships, which is 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).[18] A link exists between two friends if at least one of the two individuals has identified the other as his/her best friend.[19]

17. For a detailed description of the survey and data, see the AddHealth Web site at http://www.cpc.unc.edu/projects/addhealth.

18. The limit in the number of nominations is not binding, not even by gender. Less than 1% of the students in our sample show a list of 10 best friends, less than 3% a list of five males and roughly 4% name five females. On average, they declare to have 6.04 friends with a small dispersion around this mean value (SD equal to 1.32).

19. Note that, when an individual i identifies a best friend j who does not belong to the surveyed schools, the database does not include j in the network of i; it provides no information about j. Fortunately, in the large majority of cases (more than 93%), best friends tend to be in the same school and thus are systematically included in the network.

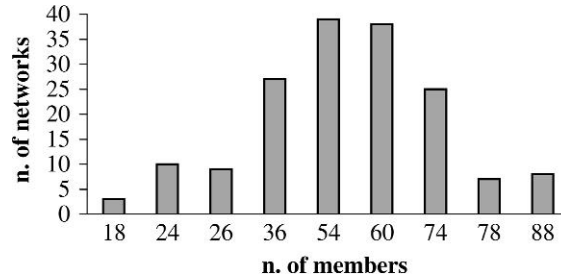


Figure 1. The Empirical Distribution of Adolescent Networks.

Figure 1 shows the empirical distribution of friendship networks in our sample by their size (i.e., the number of network members).[20] It appears that most friendship networks have between 36 and 74 members. The minimum number of friends in a network is 18, whereas the maximum is 88. The average and the SD of network size are 49.51 and 16.80.

By matching the identification numbers of the friendship nominations to respondents' identification numbers, one can obtain information on the characteristics of nominated friends.

Besides information on family background, school quality, and area of residence, the AddHealth contains sensitive data on sexual behavior (contraception, pregnancy, and AIDS risk perception), tobacco, alcohol, drugs, and crime of a subset of adolescents. We use these data to construct our dependent variable e_i. AddHealth contains an extensive set of questions on juvenile delinquency, ranging from light offenses that only signal the propensity toward a delinquent behavior to serious property and violent crime.[21] First, we adopt the standard approach in the sociological literature to derive an index of delinquency involvement based on self-reported adolescents' responses to a set of questions describing participation in a series of criminal activities. The survey asks students how often they participate in each of the different activities during the past year.[22] Each response is coded using an ordinal scale ranging

20. 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 networks having number of members between the i and $i-1$ percentile.

21. Specifically, it contains information on 15 delinquency items. Namely, paint graffiti or signs on someone else's property or in a public place; deliberately damage property that did not belong to you; lie to your parents or guardians about where you had been or whom you were with; take something from a store without paying for it; get into a serious physical fight; hurt someone badly enough to need bandages or care from a doctor or nurse; run away from home; drive a car without its owner's permission; steal something worth more than $50; go into a house or building to steal something; use or threaten to use a weapon to get something from someone; sell marijuana or other drugs; steal something worth less than $50; take part in a fight where a group of your friends was against another group; act loud, rowdy, or unruly in a public place.

22. Respondents listened to pre-recorded questions through earphones and then they entered their answers directly on laptop computers. This administration of the survey for sensitive topics minimizes the potential for interview and parental influence while maintaining data security.

from 0 (i.e., never participate) to 1 (i.e., participate one or two times), 2 (participate three or four times) up to 3 (i.e., participate five or more times). On the basis of these variables, a composite score is calculated for each respondent.[23] The mean is 1.03, with considerable variation around this value (the SD is equal to 1.22). The Crombach-α measure is then used to assess the quality of the derived index. In our case, we obtain an α equal to 0.76 ($0 \leqslant \alpha \leqslant 1$) indicating that the different items incorporated in the index have considerable internal consistency. Second, in Section 4.2 we consider different categories of crime, which are chosen accordingly to the seriousness of the crime committed. Using the corresponding information for nominated friends, we are able, for each individual i, to calculate the average crime effort $\bar{e}_i$ of his/her peer group. Excluding the individuals with missing or inadequate information, we obtain a final sample of 9322 students distributed over 166 networks.[24]

3.2 Empirical Strategy

Guided by Proposition 2, our aim is to assess the actual empirical relationship between the group criminal effort $\bar{e}_i$ and individual effort level e_i^* (comparative statics result; equation (7)).

The main novel feature of our estimation with respect to previous works is the use of the architecture of networks to evaluate peer effects. Let us explain this more clearly.

3.2.1 Reflection Problem.

In linear-in-means models, simultaneity in behavior of interacting agents introduces a perfect collinearity between the expected mean outcome of the group and its mean characteristics. Therefore, it is difficult to differentiate between the effect of peers' choice of effort and peers' characteristics that do impact on their effort choice (the so-called *reflection problem*; Manski 1993). Basically, the reflection problem arises because, in the standard approach, individuals interact in groups, that is, individuals are affected by all individuals belonging to their group and by nobody outside the group. In other words, groups do overlap. In the case of social networks, instead, this is nearly never true since the reference group is the number of friends each individual has. So, for example, take individuals i and k such that $g_{ik} = 1$. Then individual i is directly influenced by $g_i = \sum_{j=1}^{n_i} g_{ij} e_j$, whereas individual k is directly influenced by $g_k = \sum_{j=1}^{n_k} g_{kj} e_j$, and there is little chance for these two values to be the same unless the network is complete (i.e., everybody is linked with everybody). Formally, social effects are identified (i.e., no reflection problem) if $\mathbf{G}^2 \neq \mathbf{0}$, where $\mathbf{G}^2$ keeps track of indirect connections of length

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

24. The networks include both criminals and noncriminals.

2 in $\mathbf{g}$.[25] This condition guarantees that $\mathbf{I}$, $\mathbf{G}$ and $\mathbf{G}^2$ are linearly independent. $\mathbf{G}^2 \neq \mathbf{0}$ means that there exist at least a path of length 2 between two individuals.[26] In other words, if i and j are friends and j and k are friends, it does not necessarily imply that i and k are also friends. Even in linear-in-means models, the Manski's (1993) reflection problem is thus eluded. These results are formally derived in Bramoullé et al. (2009) (see, in particular, Proposition 3) and used in Calvó-Armengol et al. (2009). Cohen-Cole (2006) presents a similar argument, that is, the use of outgroup effects, to achieve the identification of the endogenous group effect in the linear-in-means model (see also Weinberg et al. 2004; Lin 2008; Laschever 2009).

3.2.2 Endogenous Network Formation/Correlated Effects. Although this setting allows us to solve the reflection problem, the estimation results might still be flawed because of the presence of unobservable factors affecting both individual and peer behavior. It is thus difficult to disentangle the endogenous peer effects from the correlated effects, that is, from effects arising from the fact that individuals in the same group tend to behave similarly because they face a common environment. If individuals are not randomly assigned into groups, this problem might originate from the possible sorting of agents. If the variables that drive this process of selection are not fully observable, potential correlations between (unobserved) group-specific factors and the target regressors are major sources of bias. In our case, two types of possibly correlated effects arise, that is, at the network level and at the peer group level. The use of network fixed effects proves useful in this respect. Assume, indeed, that agents self-select into different networks in a first step and that link formation takes place within networks in a second step. Then, as Bramoullé et al. (2009) observe, if linking decisions are uncorrelated with the observable variables, this two-step model of link formation generates network fixed effects. Assuming additively separable network heterogeneity, a within-group specification is able to control for these correlated effects. In other words, we use a model specification with a network-specific component of the error term and adopt a traditional (pseudo) panel data fixed-effects estimator, namely, we subtract from the individual-level variables the network average.[27]

25. The coefficient $g_{ij}^{[2]}$ in the (i, j) cell of $\mathbf{G}^2$ gives the number of paths of length 2 in $\mathbf{g}$ between i and j.

26. It is extremely rare that in the real world the condition $\mathbf{G}^2 \neq \mathbf{0}$ is not satisfied since it would basically imply that all networks are complete. In our data set, where 166 networks are considered (see above in Section 3.1), none of them are complete and all satisfy the condition that guarantees the identification of social effects.

27. Bramoullé et al. (2009) also deal with this problem in the context of networks. In their Proposition 5, they show that if the matrices $\mathbf{I}$, $\mathbf{G}$, $\mathbf{G}^2$, and $\mathbf{G}^3$ are linearly independent, then by subtracting from the variables the network component average (or the average over neighbors, i.e., direct friends) social effects are again identified and one can disentangle endogenous effects from correlated effects. In our data set, this condition of linear independence is always satisfied.

Observe that our particularly large information on individual (observed) variables should reasonably explain the process of selection into groups. Then the inclusion of network fixed effects acts as a further control for possible sorting effects based on unobservables.

To document to what extent this approach accounts for self-selection in our case, we need to provide evidence that (a) network fixed effects account for unobservable factors driving the allocations of agents into networks and (b) once observables and network fixed effects are controlled for linking decisions are uncorrelated with peer-level observables. In other words, (b) should show that, conditional upon network fixed effects, student and peer characteristics are orthogonal, thus indicating that peer group formation is random conditional upon network.

We thus consider individual variables that are commonly believed to induce self-selection into teenagers' friendship groups and perform two different exercises. First, we estimate the correlations between such individual-level variables and the network averages of the residuals obtained from a regression analysis where the influence of a variety of other factors (see Table B1, Appendix B, for a precise description of variables) and network fixed effects are washed out. Second, we estimate the correlations between such individual-level variables and peer group averages (i.e., averages over best friends), once the influence of our extensive set of controls and network fixed effects are washed out. The results are reported in Table 1 (in the second and third columns, respectively).[28] The estimated correlation coefficients are not statistically significant for all attributes considered in both columns. This indicates that, in our case, (a) the particularly large information on individual (observed) variables and (additively separable) unobserved network characteristics account for a possible sorting of students into networks and (b) conditionally on individual and network characteristics, linking decisions are uncorrelated with observable variables.[29]

28. More formally, in the first exercise, we estimate the ordinary least square (OLS) residuals from the equation

$$y_{i,\kappa} = \sum_{m=1}^{M} \beta_1^m x_{i,\kappa}^m + \frac{1}{g_{i,\kappa}} \sum_{m=1}^{M} \sum_{j=1}^{n_\kappa} \theta_m g_{ij,\kappa} x_{j,\kappa}^m + \eta_k + \varepsilon_{ik}, \tag{12}$$

where $y_{i,k}$, is a given characteristic of individual i in network κ, $x_{i,\kappa}^m$ (for $m = 1, \ldots, M$) is the set of M control variables containing an extensive number of individual, family, school, and residential area characteristics, $\sum_{j=1}^{n_\kappa} (g_{ij,\kappa} x_{j,\kappa}^m)/g_{i,\kappa}$ is the set of the average values of the M controls of i's direct friends, η_k denote network fixed effects, and ε_{ik} the random error term. We then report in the first column of Table 1 the OLS estimates that are obtained when regressing $y_{i,\kappa}$ on the residuals $\widehat{\varepsilon}_{ik}$ averaged over networks. In the second column, instead, we report the estimated $\theta_m s$ associated to $x_{j,\kappa}^m = y_{i,\kappa}$.

29. The architecture of social networks with nonoverlapping groups also offers the opportunity for instrumental variable estimation to control for peer group correlated effects. Since individual $k \notin g_i$, the characteristics of k do not directly affect e_i (i's outcome) but, since $k \in g_j$, they affect e_j (j's outcome), and since $j \in g_i$, e_j affects e_i. As a result, the characteristics of k affects e_i only *indirectly* through its effect on e_j. This means that the characteristics of k are a valid instrument to estimate the endogenous social effect for e_i. We experimented with different sets of instruments

Table 1. Correlation Between Individual, Network, and Peer Group–Level Variables

Individual variables	Correlation with network-averaged residuals	Correlation with peer group–averaged variables
Parental education	−0.1996	0.0725
	(0.3417)	(0.1198)
Parental care	0.1562	−0.1662
	(0.1631)	(0.2217)
Mathematics score	−0.1819	0.0699
	(0.2042)	(0.0755)
Motivation in education	−0.0896	0.1546
	(0.2577)	(0.1869)
School attachment	0.0725	0.0499
	(0.0993)	(0.0763)
Social exclusion	0.0317	−0.0901
	(0.0341)	(0.1008)
Individual sociodemographic variables	Yes	Yes
Family background variables	Yes	Yes
Protective factors	Yes	Yes
Residential neighborhood variables	Yes	Yes
Contextual effects	Yes	Yes
School dummies	Yes	Yes
Network fixed effects	Yes	Yes

OLS estimates and SE (in parentheses) are reported.
The model specification is detailed in the text (footnote 22).
Control variables are those listed in Table B1.
Regressions include weights to control for the AddHealth survey design.
None of the coefficients is statistically significant at any conventional level.

3.2.3 Correlated Individual Effects. Finally, one might question the presence of problematic unobservable factors that are neither network specific nor peer group specific, but rather individual specific. In this respect, the richness of the information provided by the AddHealth questionnaire on adolescents' behavior allow us to find proxies for typically unobserved individual characteristics that may be correlated with our variable of interest. Specifically, to control for differences in leadership propensity across adolescents, we include an indicator of self-esteem and an indicator of the level of physical development compared to the peers, and we use mathematics score as an indicator of ability. Also, we attempt to capture differences in attitude toward education and parenting by including indicators of the student's motivation in education and parental care.

3.2.4 Correlated School Effects. Similar arguments can be put forward for the existence of possible correlations between our variable of interest and

(different characteristics of excluded friends), but our results, that is, our estimates of peer effects, remain always qualitatively unchanged.

unobservable school characteristics affecting structure and/or quality of school-friendship networks in analyzing students' school performance. Because the AddHealth survey interviews all children within a school, we estimate our model conditional on school fixed effects (i.e., we incorporate in the estimation *school dummies*). This approach enables us to capture the influence of school-level inputs (such as teachers and students quality, and possibly the parents' residential choices), so that only the variation in the average behavior of peers (across students in the same school) would be exploited.[30]

3.2.5 Deterrence Effects. So far in this section, we have focused our attention on the main purpose of our empirical analysis, which is to be found in the identification of peer effects and conformism in crime using the network architecture. The identification of deterrence effects (pf in our theoretical model) on crime is an equally difficult empirical exercise because of the well-known potential simultaneity and reverse causality issues (Levitt 1997), which cannot be totally solved using our network-based empirical strategy. School dummies, however, also account for differences in the strictness of anticrime regulations across schools (i.e., differences in the expected punishment for a student who is caught possessing illegal drug, stealing school property, verbally abusing a teacher, etc.) as well as for differences in crime policies at the local level (because schools are in different areas). As a result, instead of directly estimating deterrence effects (i.e., to include in the model specification observable measures of deterrence, such as local police expenditures or the arrest rate in the local area), we focus our attention on the estimation of peer effects in crime, accounting for observable and unobservable school, and hence area-of-residence, variables (such as policing practicing, ethnic concentration, low informal social control, lack of educational or economic opportunities, etc.) that might be correlated with our variable of interest.

Assuming n_κ individuals in each of the K networks in the economy, for $i = 1, \ldots, n_\kappa$, $\kappa = 1, \ldots, K$, and using equation (3), the econometric counterpart of equation (6) is given by

$$e_{i,\kappa} = \phi \frac{1}{g_{i,\kappa}} \sum_{j=1}^{n_{i,\kappa}} g_{ij,\kappa} e_{j,\kappa} + \sum_{m=1}^{M} \beta_1^m x_{i,\kappa}^m + \frac{1}{g_{i,\kappa}} \sum_{m=1}^{M} \sum_{j=1}^{n_\kappa} \theta_m g_{ij,\kappa} x_{j,\kappa}^m + \eta_k + \varepsilon_{ik}, \quad (10)$$

where $e_{i,k}$, is the index of criminality of individual i in network κ, $x_{i,\kappa}^m$ (for $m = 1, \ldots, M$) is the set of M control variables containing an extensive number of individual, family, school, and residential area characteristics, $g_{i,\kappa} = \sum_{j=1}^{n_\kappa} g_{ij,\kappa}$ is the number of direct links of i, $\sum_{j=1}^{n_\kappa} (g_{ij,\kappa} x_{j,\kappa}^m)/g_{i,\kappa}$ is the set of the average values of the M controls of i's direct friends (i.e., contextual effects). As stated in the theoretical model, $\sum_{m=1}^{M} \beta_1^m x_{i,\kappa}^m + \frac{1}{g_{i,\kappa}} \sum_{m=1}^{M} \sum_{j=1}^{n_\kappa} \gamma_m g_{ij,\kappa} x_{j,\kappa}^m$ reflects the ex ante idiosyncratic heterogeneity of

30. Most of the times (but not always) school dummies coincide with network dummies. The introduction of student grade or student year of attendance dummies does not change qualitatively the results on our target variable.

each individual i, and our measure of *taste for conformity* or *strength of peer effects* is captured by the parameter ϕ (in the theoretical model $\phi = d/(c+d)$). To be more precise, $\phi = d/(c+d)$ measures the taste for conformity relative to the direct, time or psychological costs of crime (captured by the parameter c). So if c were very small, ϕ would be positive and large even if the taste for conformity (d) were very small. Finally, the error term consists of a network-specific component (constant over individuals in the same network), which might be correlated with the regressors, η_k, and a white noise component, ε_{ik}. A precise description of the variables included and the corresponding descriptive statistics are contained in the Data Appendix to this article (Table B1, Appendix B).

Model (10) is the empirical equivalent of the first-order conditions of our model of network peer effects given by equation (6) in Proposition 2. It is the so-called *spatial lag model* or *mixed-regressive spatial autoregressive model* (Anselin 1988) with the addition of a network-specific component of the error term. Once the variables are transformed in deviations from the network-specific means, a maximum likelihood approach (see, e.g., Anselin 1988) allows us to estimate jointly $\widehat{\boldsymbol{\beta}}$, $\widehat{\boldsymbol{\gamma}}$, and $\widehat{\phi}$.

4. Empirical Results

4.1 Testing the Model

The maximum likelihood estimation results of model (10) are reported in the second column of Table 2 ("All crimes").[31] The table shows that the estimated coefficient of ϕ, which measures the *taste for conformity*, is statistically significant and has a positive sign. Specifically, a one SD increase in individual i's taste for conformity or equivalently in the average criminal activity of individual i's reference group raises individual i's level of crime by about 5.2% of an SD. This evidence supports our theoretical framework predicting a relevant role of peers and conformity to peers' behavior in shaping criminal activities among teenagers.

4.2 Different Types of Crime

The literature on local interactions has uncovered some interesting differences between different types of crime. For instance, Ludwig et al. (2000) find that neighborhood effects are large and negative for violent crime but have a mild positive effect on property crime. In contrast, Glaeser et al. (1996) find instead that social interactions seem to have a large effect on petty crime, a moderate effect on more serious crime, and a negligible effect on very violent crime.

The basic idea of our theoretical model is that agents' criminal behavior is driven by their desire to reduce the discrepancy between their own crime effort

31. When the model is estimated with an increasing set of controls (i.e., by adding the different groups listed in Table B1), the value of $\widehat{\phi}$ decreases, thus indicating that we are capturing important confounding factors. However, the qualitative results remain unchanged. The complete list of estimation results is available upon request.

Table 2. Maximum Likelihood Estimation Results Dependent Variable: Delinquency Index

	All crimes	Type 1	Type 2	Type 3
Conformism/peer effects (ϕ)	0.0612** (0.0305)	0.0688** (0.0320)	0.0499** (0.0241)	0.0079** (0.0035)
Individual sociodemographic variables	Yes	Yes	Yes	Yes
Family background variables	Yes	Yes	Yes	Yes
Protective factors	Yes	Yes	Yes	Yes
Residential neighborhood variables	Yes	Yes	Yes	Yes
Contextual effects	Yes	Yes	Yes	Yes
School dummies	Yes	Yes	Yes	Yes
Network fixed effects	Yes	Yes	Yes	Yes
Pseudo-R^2	0.4766	0.4915	0.4111	0.4599

Estimated coefficients and SEs (in parentheses) are reported.
Estimation using Spacestat v1.93 (Anselin 1995).
Control variables are those listed in Table B1.
Regressions include weights to control for the AddHealth survey design.
**Statistical significance at the 5% level.

and that of their reference group (i.e., their best friends). We find that such a model is validated by our data for juvenile crime as a whole.

The richness of the information provided by the AddHealth data on juvenile crime enables us also to test our conformism model for different types of crime, thus making our analysis directly comparable to previous works. Specifically, we analyze whether the magnitude of the peer effects depends on the type of crime committed. We split the offences reported in our data in three groups (with increasing costs of committing crime). The first group (*type-1 crimes*) contains (a) to paint graffiti or sign on someone else's property or in a public place, (b) to lie to the parents or guardians about where or with whom having been, (c) to run away from home, and (d) to act loud, rowdy, or unruly in a public place. The second group (*type-2 crimes*) consists of (a) to get into a serious physical fight, (b) to hurt someone badly enough to need bandages or care from a doctor or nurse, (c) to drive a car without its owner's permission, and (d) to steal something worth less than $50. The third group (*type-3 crimes*) encompasses (a) to take something from a store without paying for it, (b) to steal something worth more than $50, (c) to go into a house or building to steal something, (d) to use or threat to use a weapon to get something from someone, and (e) to sell marijuana or other drugs. Less than 20% of the teenagers in our sample confess to have committed the more serious offences.[32] To be precise, these three groups contain 3488, 4084, and 1803 individuals, respectively.

32. Adolescents are selected in a more serious type of crime group if they have committed at least one of the offences considered in the group.

We estimate the following modified version of model (10):

$$e_{i,\kappa,l} = \alpha\phi_l \sum_{j=1}^{n_{i,\kappa}} g_{ij,\kappa} e_{j,\kappa} + \sum_{m=1}^{M} \beta^m x_{i,\kappa}^m + \frac{1}{g_{i,\kappa}} \sum_{m=1}^{M} \sum_{j=1}^{n_\kappa} \theta_m g_{ij,\kappa} x_{j,\kappa}^m + \eta_k + \varepsilon_{i,k,l}, \quad (11)$$

where $e_{i,\kappa,l}$ is now the index of crime of type l committed by individual i in network κ, and the rest of the notation defined for model (10) applies. The estimation of this model provides type of crime-specific peer effects. The results are contained in columns 3, 4, and 5 of Table 2. We find that the estimated coefficient ϕ_l, which measures the taste for conformity for type-l crime, remains always significant and positive whatever the seriousness of the crime considered, but it decreases in magnitude when moving from light to more serious crimes. A one SD increase in individual i's taste for conformity for type-1 crimes or equivalently a one SD increase in the average criminal activity of individual i's reference group translates roughly into a 9.8% decrease in SDs of individual i's criminal activity when petty crimes (type-1 crimes) are considered, whereas this effect amounts to 6.3 and only to 1.4 for intermediary (type-2 crimes) and serious crimes (type-3 crimes), respectively. This evidence is in line with the findings of Glaeser et al. (1996) who show that social interactions are more important for petty crimes.

5. Robustness Check: Undirected Versus Directed Networks

Our theoretical model and consequently our empirical investigation assume so far that friendship relationships are symmetric, that is, $g_{ij,\kappa} = g_{ji,\kappa}$. In this section, we check how sensitive our results are to such an assumption, that is, to a possible measurement error in the definition of the peer group. Indeed, our data make it possible to know exactly who nominates whom in a network, and we find that 12% of relationships in our data set are not reciprocal. Instead of constructing undirected network, we will now focus on the analysis of directed delinquent networks.

In the language of graph theory, in a directed graph, a link has two distinct ends: a head (the end with an arrow) and a tail. Each end is counted separately. The sum of head end points count toward the *indegree* and the sum of tail end points count toward the *outdegree*. Formally, we denote a link from i to j as $g_{ij} = 1$ if j has nominated i as his/her friend, and $g_{ij} = 0$, otherwise. The indegree of student i, denoted by g_i^+, is the number of nominations student i receives from other students, that is, $g_i^+ = \sum_j g_{ij}$. The outdegree of student i, denoted by g_i^-, is the number of friends student i nominates, that is, $g_i^- = \sum_j g_{ji}$. We can thus construct two types of directed networks, one based on indegrees and the other based on outdegrees. Observe that, by definition, whereas in undirected networks the adjacency matrix $\mathbf{G} = [g_{ij}]$ is *symmetric*, in directed networks, it is *asymmetric*.

Table 3. Maximum Likelihood Estimation Results Dependent Variable: Delinquency Index—Directed Networks Using Indegrees

	All crimes	Type 1	Type 2	Type 3
Conformism/peer effects (ϕ)	0.0565** (0.0279)	0.0612** (0.0283)	0.0451** (0.0206)	0.0067** (0.0034)
Individual sociodemographic variables	Yes	Yes	Yes	Yes
Family background variables	Yes	Yes	Yes	Yes
Protective factors	Yes	Yes	Yes	Yes
Residential neighborhood variables	Yes	Yes	Yes	Yes
Contextual effects	Yes	Yes	Yes	Yes
School dummies	Yes	Yes	Yes	Yes
Network fixed effects	Yes	Yes	Yes	Yes
Pseudo-R^2	0.4529	0.4801	0.4001	0.4455

Estimated coefficients and SEs (in parentheses) are reported.
Estimation using Spacestat v1.93 (Anselin 1995).
Control variables are those listed in Table B1.
Regressions include weights to control for the AddHealth survey design.
**Statistical significance at the 5% level.

From a theoretical point of view, it is easily verified that, in the Proof of Propositions 1 and 2, the symmetry of **G** does not play any explicit role and thus all the results remain valid with a nonsymmetric **G**.

Turning to the empirical analysis, we report in column 2 of Tables 3 and 4 the results of the estimation of model (10) and of its modified version (11) when the directed nature of the network data is taken into account. It appears that our results are only minimally affected in both tables. The estimated peer effects

Table 4. Maximum Likelihood Estimation Results Dependent Variable: Delinquency Index—Directed Networks Using Outdegrees

	All crimes	Type 1	Type 2	Type 3
Conformism/peer effects (ϕ)	0.0609*** (0.0216)	0.0669** (0.0290)	0.0472** (0.0203)	0.0070** (0.0031)
Individual sociodemographic variables	Yes	Yes	Yes	Yes
Family background variables	Yes	Yes	Yes	Yes
Protective factors	Yes	Yes	Yes	Yes
Residential neighborhood variables	Yes	Yes	Yes	Yes
Contextual effects	Yes	Yes	Yes	Yes
School dummies	Yes	Yes	Yes	Yes
Network fixed effects	Yes	Yes	Yes	Yes
Pseudo-R^2	0.4790	0.5088	0.4215	0.4633

Estimated coefficients and SEs (in parentheses) are reported.
Estimation using Spacestat v1.93 (Anselin 1995).
Control variables are those listed in Table B1.
Regressions include weights to control for the AddHealth survey design.
**Statistical significance at the 5% level.

remain positive and statistically significant. They are only slightly lower in magnitude.

6. Conclusion and Policy Implications

In education, crime, smoking, teenage pregnancy, school dropout, etc., economists have pointed out the importance of peer effects in explaining these outcomes (see, e.g., Glaeser and Scheinkman 2001). Understanding the generating mechanism of such peer effects is essential for the interpretation of the findings and to provide policy guidance. We believe that conformity is the key element determining economic outcomes that involve interactions with peers. In the present article, we propose a model that explains how conformity and deterrence impact on criminal activities. In particular, we find significant impact of peers on individual criminal activity for individuals belonging to the same group of friends. We then test the model using the US National Longitudinal Survey of Adolescent Health (AddHealth), which contains unique detailed information on friendship relationships among delinquent teenagers. A "reversion-to-the-group-mean" effect is identified.

Our results suggest that, for teenagers, the decision to commit crime depends on the seriousness of crime. In particular, for petty crimes, adolescents are strongly affected by their environment and peers because of externalities involved in social decision making. In their study of a gang located in a black inner-city neighborhood, Levitt and Venkatesh (2000) find that "social/nonpecuniary factors are likely to play an important role" in criminal decisions and gang activities. Here, even though we do not focus on gangs, we highlight one of these social/nonpecuniary factors: the desire to conform to the group's norm. Because of the implications of juvenile crime for adolescent's behavior in the future, an effective policy should be measured not only by the possible crime reduction it implies but also by the group interactions it engenders.

To be more precise, if social interactions and conformism are crucial to understand juvenile criminal activities, then a targeted policy identifying "key players" (or "key groups of players") in a given area (Ballester et al. 2006, 2010) may be an effective way to reduce crime. A key player (or a key group) is an individual (or a group of persons) belonging to a network of criminals who, once removed, leads to the highest aggregate delinquency reduction. In practice, the planner may want to identify optimal network targets to concentrate (scarce) investigatory resources on some particular individuals, or to isolate them from the rest of the group, either through leniency programs, social assistance programs, or incarceration. The success of such policy depends on the ability to identify a social network, and this task may be not as difficult as it seems to be. For instance, Haynie (2001) and the present article use friendship data to identify delinquent peer networks for adolescents in the United States that participated in an in-school survey in the 1990s. Sarnecki (2001) provides a comprehensive study of co-offending relations and corresponding network structure for football hooligans and right-wing extremists in Stockholm. In all

these cases, one may directly use the available data to determine the key player or group players.

Social mixing policies, like the MTO experiment (mentioned in Section 1), which relocates families from high- to low-poverty neighborhoods, could also be an effective tool in breaking delinquent networks. Indeed, by moving "key" delinquents (or "key groups" of delinquents) from one area to another, this policy will disrupt the communication and the links between delinquents in a given network. As a result, by using together a key player (or a key group) policy and the MTO program, that is, moving families whose delinquents are "key" in a local network, would have a very efficient effect in reducing crime because they move "key" delinquents to richer areas while breaking criminal networks in poorer areas.

Appendix A

Proofs of Propositions of the Model

Proof of Proposition 1. First, observe that $\mathbf{\Gamma}$ is a stochastic matrix, that is, $\gamma_{ij}^{[k]} \geqslant 0$ and $\sum_j \gamma_{ij}^{[k]} = 1$, and thus the largest eigenvalue of $\mathbf{\Gamma}$ is 1, that is, $\mu_1(\mathbf{\Gamma}) = 1$. Second, by plugging equation (1) in equation (2), for the case $b_i = b$, we obtain

$$\begin{aligned} u_i(e_i, \bar{e}_i) &= a + be_i - pe_i f - ce_i^2 - d(e_i - \bar{e}_i)^2 \\ &= a + be_i - pe_i f - ce_i^2 - d\left[e_i - \sum_{j=1}^{j=n_i(\mathbf{g})} \gamma_{ij} e_j\right]^2 \\ &= a - d\left[\sum_{j=1}^{j=n_i(\mathbf{g})} \gamma_{ij} e_j\right]^2 + (b - pf)e_i - (c+d)e_i^2 + 2d \sum_{j=1}^{j=n_i(\mathbf{g})} \gamma_{ij} e_i e_j. \end{aligned}$$

Now, assuming $b > pf$, we can apply Theorem 1 of Ballester et al. (2006)[33] with $\alpha = b - pf$, $\beta = 2(c+d)$, $\gamma = 0$,[34] and $\lambda = 2d$. Hence, the condition for existence and uniqueness of a Nash equilibrium can be written as $2(c+d) > 2d$, which is always satisfied since $c > 0$. Third, let us calculate the Bonacich vector. By definition,

$$\begin{aligned} \eta_i(\phi, \boldsymbol{\gamma}) &= m_{ii}(\boldsymbol{\gamma}, \phi) + \sum_{j \neq i} m_{ij}(\boldsymbol{\gamma}, \phi) \\ &= \phi \sum_{j=1}^{n} \gamma_{ij} + \cdots + \phi^k \sum_{j=1}^{n} \gamma_{ij}^{[k]} + \cdots \\ &= \sum_{j=1}^{+\infty} \phi^k \end{aligned}$$

33. Observe that the term $a - d\left[\sum_{j=1}^{j=n_i(\mathbf{g})} \gamma_{ij} e_j\right]^2$ does not matter since the derivative of this term with respect to e_i is equal to zero.

34. This is the γ in Ballester et al. (2006).

since $\mathbf{\Gamma}$, $\mathbf{\Gamma}^1,\ldots,$ $\mathbf{\Gamma}^k,\ldots$ are stochastic matrices and thus $\sum_{j=1}^{n}\gamma_{ij} = \cdots = \sum_{j=1}^{n}\gamma_{ij}^{[k]} = 1$. As a result,

$$\eta_i(\phi,\gamma) = \sum_{j=1}^{+\infty}\phi^k = \frac{1}{1-\phi}.$$

Applying again Theorem 1 in Ballester et al. (2006), where $\phi = d/(c+d)$, our Nash equilibrium is given by

$$\mathbf{e}^* = \begin{pmatrix} \frac{b-pf}{2c} \\ \vdots \\ \frac{b-pf}{2c} \end{pmatrix}.$$

This implies that $\mathbf{e}^* = \bar{\mathbf{e}}^*$ and thus all players provide the same effort level $(b-pf)/(2c)$. □

Proof of Proposition 2. First, observe that $\mathbf{\Gamma}$ is a stochastic matrix $\left(\gamma_{ij} \geqslant 0 \text{ and } \sum_j \gamma_{ij} = 1\right)$ and thus its largest eigenvalue is 1, that is, $\mu_1(\mathbf{\Gamma}) = 1$. Second, as for the proof of Proposition 1, we have

$$u_i(e_i,\bar{e}_i) = a + b_i e_i - p e_i f - c e_i^2 - d_i(e_i-\bar{e}_i)^2$$

$$= a - d_i\left[\sum_{j=1}^{j=n}\gamma_{ij}e_j\right]^2 + (b_i - pf)\,e_i - (c+d_i)\,e_i^2 + 2d_i\sum_{j=1}^{j=n}\gamma_{ij}e_i e_j.$$

Assume that $b_i > pf$ for all i. The utility function is nearly the same as the one in Ballester et al. (2006),[35] where $\alpha_i = b_i - pf$, $\beta = 2(c+d)$, $\gamma = 0$,[36] and $\lambda = 2d_i$. The main difference is that we now have ex ante heterogeneity because of α_i. However, because $\gamma = 0$ (i.e., there is no global substitutability), the condition for existence and uniqueness of a Nash equilibrium is still given by $\beta > \gamma\mu_1(\mathbf{\Gamma})$,[37] which in our case is equivalent to $2(c_i+d) > 2d$ for each i. This is always satisfied since $c_i > 0$ for all i. Third, equation (6) is just the first-order condition for each individual i. □

35. Observe that the term $a - d\left[\sum_{j=1}^{j=n_i(\mathbf{g})}\gamma_{ij}e_j\right]^2$ does not matter since the derivative of this term with respect to e_i is equal to zero.

36. This is the γ in Ballester et al. (2006).

37. See Calvó-Armengol et al. (2009).

Appendix B
Data Appendix

Table B1. Description of Data (9322 individuals, 166 networks)

	Variable definition	Mean	SD	Minimum	Maximum
Delinquency index	In the text	1.03	1.22	0	3
Delinquency index of best friends	Average value of the delinquency index over direct friends	1.01	1.04	0	3
Delinquency index (type-1 crime)	In the text	1.66	1.15	0	3
Delinquency index (type-2 crime)	In the text	0.98	0.78	0	3
Delinquency index (type-3 crime)	In the text	0.59	0.33	0	3
Individual sociodemographic variables					
Female	Dummy variable taking value one if the respondent is female	0.40	0.34	0	1
Age	Respondents' age measured in years	15.25	1.85	10	19
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	3.03	1.74	0	4
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	2.69	0.78	0	4
Black or African American	Race dummies. "White" is the reference group	0.20	0.31	0	1
Race dummies. White Other races	,,	0.10	0.13	0	1
School attendance	Number or years the respondent has been a student at the school	3.29	1.86	1	6
Student grade	Grade of student in the current year	9.24	3.14	6	13

Continued

Table B1. *Continued*

	Variable definition	Mean	SD	Minimum	Maximum
Mathematics score	Score in mathematics at the most recent grading period, coded as 1 = D or lower, 2 = C, 3 = B, 4 = A	1.94	1.31	1	4
Organized social participation	Dummy taking value one if the respondent participates in any clubs, organizations, or teams at school in the school year	0.65	0.20	0	1
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 do not try very hard, 3 = I try hard enough, but not as hard as I could, 4 = I try very hard to do my best	2.24	0.88	1	4
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	3.12	2.51	1	5
Self-esteem	Response to the question: "Compared with other people your age, how intelligent are you," coded as 1 = moderately below average, 2 = slightly below average, 3 = about average, 4 = slightly above average, 5 = moderately above average, 6 = extremely above average	3.93	1.37	1	6
Family background variables					
Household size	Number of people living in the household	3.50	1.73	1	6
Two married parent family	Dummy taking value one if the respondent lives in a household with two parents (both biological and nonbiological) that are married	0.42	0.57	0	1
Single parent family	Dummy taking value one if the respondent lives in a household with only one parent (both biological and nonbiological)	0.22	0.43	0	1
Public assistance	Dummy taking value one if either the father or the mother receives public assistance, such as welfare	0.12	0.16	0	1
Mother working	Dummy taking value one if the mother works for pay	0.64	0.45	0	1

Parent education	Schooling level of the (biological or nonbiological) parent who is living with the child, distinguishing between "never went to school," "not graduate from high school," "high school graduate," "graduated from college or a university," "professional training beyond a 4-year college," coded as 1–5. We consider only the education of the father if both parents are in the household	3.58	2.08	1	5
Parents age	Mean value of the age (years) of the parents (biological or non biological) living with the child	40.14	13.64	33	75
Parent occupation manager	Parent occupation dummies. Closest description of the job of (biological or nonbiological) parent that is living with the child is manager. If both parents are in the household, the occupation of the father is considered. "Doesn't work without being disables" is the reference group	0.11	0.13	0	1
Parent occupation professional/technical	Parent occupation dummies. Closest description of the job of (biological or nonbiological) parent that is living with the child is manager. If both parents are in the household, the occupation of the father is considered. "Doesn't work without being disables" is the reference group	0.09	0.22	0	1
Parent occupation office or sales worker	Parent occupation dummies. Closest description of the job of (biological or nonbiological) parent that is living with the child is manager. If both parents are in the household, the occupation of the father is considered. "Doesn't work without being disables" is the reference group	0.25	0.29	0	1
Parent occupation manual	Parent occupation dummies. Closest description of the job of (biological or nonbiological) parent that is living with the child is manager. If both parents are in the household, the occupation of the father is considered. "Doesn't work without being disables" is the reference group	0.21	0.30	0	1
Parent occupation military or security	Parent occupation dummies. Closest description of the job of (biological or nonbiological) parent that is living with the child is manager. If both parents are in the household, the occupation of the father is considered. "Doesn't work without being disables" is the reference group	0.08	0.12	0	1

Continued

Table B1. *Continued*

	Variable definition	Mean	SD	Minimum	Maximum
Parent occupation farm or fishery	Parent occupation dummies. Closest description of the job of (biological or nonbiological) parent that is living with the child is manager. If both parents are in the household, the occupation of the father is considered. "Doesn't work without being disables" is the reference group	0.04	0.09	0	1
Parent occupation retired	Parent occupation dummies. Closest description of the job of (biological or nonbiological) parent that is living with the child is manager. If both parents are in the household, the occupation of the father is considered. "Doesn't work without being disables" is the reference group	0.06	0.10	0	1
Parent occupation other	Parent occupation dummies. Closest description of the job of (biological or nonbiological) parent that is living with the child is manager. If both parents are in the household, the occupation of the father is considered. "Doesn't work without being disables" is the reference group	0.13	0.17	0	1
Protective factors					
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	0.15	0.35	0	1
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	2.26	1.80	1	5
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-$\alpha = 0.75$)	2.57	1.75	1	5
Parental care	Dummy taking value one if the respondent reports that the (biological or nonbiological) 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	0.65	0.35	0	1

Residential neighborhood variables					
Residential building quality	Interviewer response to the question "How well kept is the building in which the respondent lives," coded as 1= very poorly kept (needs major repairs), 2= poorly kept (needs minor repairs), 3= fairly well kept (needs cosmetic work), 4= very well kept	2.96	1.85	1	4
Neighborhood safety	Dummy variable taking value if the interviewer felt concerned for his/her safety when he/she went to the respondent's home	0.52	0.57	0	1
Residential area suburban	Residential area type dummies: interviewer's description of the immediate area or street (one block, both sides) where the respondent lives. Rural area is the reference group	0.32	0.39	0	1
Residential area urban residential only	Residential area type dummies: interviewer's description of the immediate area or street (one block, both sides) where the respondent lives. Rural area is the reference group.	0.18	0.21	0	1
Residential area industrial properties—mostly wholesale	Residential area type dummies: interviewer's description of the immediate area or street (one block, both sides) where the respondent lives. Rural area is the reference group.	0.13	0.18	0	1
Residential area other type	Residential area type dummies: interviewer's description of the immediate area or street (one block, both sides) where the respondent lives. Rural area is the reference group.	0.19	0.25	0	1
Contextual effects	Average values of all the control variables over the respondent's direct friends (peer group characteristics)				

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