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ABSTRACT

Social Networks and Crime Decisions: The Role of Social Structure in Facilitating Delinquent Behaviour*

We develop a model in which delinquents compete with each other in criminal activities but may benefit from being friends with other criminals (by learning and acquiring proper know-how in the crime business). We first study the Nash equilibrium of this game by taking the social network connecting agents as given. We show that this game always has a pure strategy Nash equilibrium for generic values of the parameters. *Ex ante* identical individuals connected through a network can end up with very different equilibrium outcomes: either employed, or isolated criminal or criminals in networks. We also show that multiple equilibria with different number of active criminals and levels of involvement in crime activities may coexist and are only driven by the geometry of the pattern of links connecting criminals. We then consider a two-stage network formation and crime decisions game. We show that the multiplicity of equilibrium outcomes holds even when we allow for endogenous network formation.

JEL Classification: C72, K42 and Z13
Keywords: crime, multiple equilibria, social networks and strategic interactions

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1 Introduction

In their seminal study, Shaw and McKay (1942) show that delinquent boys in certain areas of US cities have contact not only with other delinquents who are their contemporaries but also with older offenders, who in turn had contact with delinquents preceding them, and so on ... This contact means that the traditions of delinquency can be and are transmitted down through successive generations of boys and across members of the same generation, in much the same way that language and other social forms are transmitted.

The aim of this paper is precisely to study the role of social networks and social structure in facilitating criminal behavior.

Even though there is an important literature in criminology and sociology on the social aspects of crime[1] (see e.g. Sutherland, 1947, Sarnecki, 2001 and War, 2002), surprisingly very little has been done in economics, especially from a theoretical viewpoint, to try and wedge a careful bridge between the underlying social setting where individuals are embedded, and the individual crime decisions. Two prominent exceptions are Sah (1991) and Glaeser, Sacerdote and Scheinkman (1996).[2]

Let us now describe our model. As in the standard crime model (Becker, 1968), each individual has to make a choice between becoming a criminal and participating in the labor market (these two activities being mutually exclusive) by implementing a cost-benefit analysis. Compare to the standard model, we have at least three main innovations.

First, the decision is not binary since individuals not only decide to become a criminal or not but also determine how much effort to put in criminal activities.

Second, on the benefit part, the booty is not exogenous but depends positively on the effort level of the criminal in question and negatively of the efforts of the other criminals. This is because the higher the crime level, the less that remains for a particular criminal (the fixed pie to share shrinks with the aggregate level of criminal activities).

Third, and this is our main innovation, on the cost part, criminals may benefit from being friends with other criminals or more exactly from belonging to the same network of relationships. In our framework, the social connections between criminals are modeled by means of a graph. We assume that the higher the criminal connections to a criminal and/or the higher the involvement in criminal activities of these connections, the lower his individual probability to be caught. The idea is as follows. There is no formal way of learning to become a criminal, no proper "school" providing an organized transmission of the objective skills needed to undertake successful criminal activities. Given this lack of formal institutional arrangement, we believe that the most natural and efficient way to learn to become a criminal is through the interaction with other criminals.[3] Delinquents learn from other criminals belonging to the same network how to commit

[1] To avoid monotony, the terms "crime" and "delinquency" are used interchangeably throughout this paper.

[2] We will discuss in more details these two models in section 5.

[3] Empirical evidence suggests that indeed peer effects are very strong in criminal decisions. Case and Katz (1991), using data from the 1989 NBER 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 percent more of the youths are involved in crime than in his or her initial neighborhood is to raise the probabibility the youth will become involved in crime by 2.3 percent. Ludwig *et al.* (2001) explore this last result by using data from the Moving to Opportunity (MTO) experiment that relocates families from high- to low-poverty neighborhoods. They find that this policy reduces juvenile arrests for violent offences by 30 to 50 percent of the arrest rate for control groups. This also suggests very strong social interactions in crime behaviors. Two more recent papers by Chen and Shapiro (2003) and Bayer *et al.* (2003) find also strong peer effects in crime by investigating the influence that individuals serving time in the same facility have on the subsequent criminal behavior of offenders. The

crime in a more efficient way by sharing the know-how about the "technology" of crime. In our model, we capture this local nature of the mechanism through which skills are acquired by relating the individual probability to be caught to the crime level involvement of one's direct mates, and by assuming that this probability decreases with the corresponding local aggregate level of crime. The criminology and sociology literature proposes different mechanisms according to which social ties among criminally active individuals are a means whereby the individuals in question exert an influence over one another to commit offences (e.g. social facilitation model, subdeviance local norms, etc... just to name a few). Note, though, that for the outside observer, our assumption of local know-how sharing is equivalent to many other models of local social influence in crime decisions.

This view of criminal networks and the role of peers in learning the technology of crime is not new, at least in the criminology literature. In his very influential theory of differential association, Sutherland (1947) locates the source of crime and delinquency in the intimate social networks of individuals. Emphasizing that criminal behavior is *learned* behavior, Sutherland (1947) argued that persons who are selectively or differentially exposed to delinquent associates are likely to acquire that trait as well.[4] In particular, one of his main propositions states that when criminal behavior is learned, the learning includes (*i*) techniques of committing the crime, which are sometimes very complicated, sometimes very simple, (*ii*) the specific direction of motives, drives, rationalization and attitudes. Interestingly, 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 in the delinquency literature (for surveys, see War, 1996 and Matsueda and Anderson, 1998).

One natural way of interpreting the social connections between criminals is through a gang since the latter is in general viewed as a specific type of criminal network (Sarnecki, 2001). Indeed, when individuals belong to the same gang, they learn from each other. Using data from the Rochester Youth Development study, which followed 1,000 adolescents through their early adult years, Thornberry *et al.* (1993) find that once individuals become members of a gang, their rates of delinquency increase substantially compared to their behavior before entering the gang. In other words, networks of criminals or gangs amplify delinquent behaviors. In the sociological literature, this is referred to as the *social facilitation* model, where gang members are intrinsically no different from nongang members in terms of delinquency or drug use. If they do join a gang, however, the normative structure and group processes of the gang (network) are likely to bring about high rates of delinquency and drug use. Gang membership is thus viewed as a major cause of deviant behavior. This is also what is found by Thornberry *et al.* (2003).

In the present paper, the gang interpretation of the network is possible as long as it means that the role of gangs is to facilitate the learning of crime technology to its members without implying that crimes are committed collectively as it is sometimes the case in gang activities. In other words, in our model, individuals *learn* illegal conduct from others but *practice* it alone.

These are the key ingredients of the model in which the other criminals have two opposite effects on a given criminal's (expected) utility. On the one hand, they compete in criminal activities since the higher the number of criminals, the smaller the pie to share. On the other, the higher the number of criminals that are

former shows that worsening prison conditions significantly increases post-release crime. The latter provides strong evidence that, for many types of crimes, learning is significantly enhanced by access to peers with experience with that crime.

[4] Sutherland (1947) and Akers (1998) expressly argue that criminal behavior is learned from others in the same way that *all* human behavior is learned. Indeed, young people may be influenced by their peers in all categories of behavior - music, speech, dress, sports, and *delinquency*.

connected to a given criminal, the lower is his probability to be caught because he benefits from the knowledge of the others in terms of crime efficiency. The tension between these two forces is at the heart of our model. In our framework, criminal friends (social connections) create both positive and negative externalities between each other. The competitive effect acts as a negative externality exerted by every individual criminal to every other individual in the delinquent pool. By contrast, the positive externality in the form of know-how is only exerted at the local level, among those directly connected individuals.[5] The span and intensity of this latter externality is determined by the shape of the social network and varies across individuals (and their graph locations) with the geometry of the network of links. In particular, ex ante identical individuals holding asymmetric network locations face different externality intensities. Because these externalities are at the heart of the cost-benefit analysis undertaken at the individual level, the equilibrium pattern of network decisions is likely to reflect ex post heterogeneity among individuals. In solving the tension between the two forces, the geometry of the network of connections plays a major role, that we explore.

We first study the Nash equilibrium of this game (where individuals choose their crime's effort levels) by taking the social network as given. In particular, we study the impact of the shape of the network on the crime rate in the economy. We first show that this game always has a pure strategy Nash equilibrium for generic values of the parameters. As in Becker, and not surprisingly, we find that, if punishment is sufficiently high, then individuals never choose to become a criminal and all enter the labor market. When punishment is not too high, some individuals are criminal and some are not, and the equilibrium pattern of crime decisions is carefully tailored to the underlying network geometry. In particular, different Nash equilibria with different number of active criminals and differing levels of involvement in crime activities may coexist. Note that *this multiplicity of equilibria is obtained with ex ante identical agents, and is only driven by the geometry of the pattern of links connecting them.* Note also that multiplicity of equilibria, as obtained in our model, is consistent with the high (unexplained) variance of crime levels across geographic locations (see, e.g., Glaeser *et al.* 1996).

The way we compute the Nash equilibrium is as follows. Given n agents in the economy, we start with a given graph of relationships that could have any shape. Prominent examples are the *complete graph* in which each agent is in direct relationship with every other agents so that each has $n-1$ direct contacts, the *circle* in which each agent has two direct contacts, and the *star-shaped graph* where one central agent is in direct contact with all the other peripheral agents who, in turn, are only connected to this central agent.[6] Given this initial graph of relationships on the whole population set N, we solve for the Nash equilibria in crime-effort levels exclusively (that is, without yet considering the outside option provided by the labor market) for all possible subsets of criminals S. The network of know-how sharing among a given subset $S \subset N$ of criminals is given by the network induced on S by the initial graph. The network induced on S is simply obtained by removing from the initial network all agents not in S and all links stemming from agents not in S. Then, we look at all the induced graphs of criminals that are indeed sustainable as a Nash equilibrium of our general game, where agents compare crime benefits with the outside option provided by the labor market (i.e. no unilateral deviation shall be profitable for neither type of agents, nor criminal, nor

[5] In fact, when solving for the Nash equilibria of the crime decision game, the strategic interdependence of individual decisions ruling out the equilibrium outcome within a connected set of agents causes this externality to unravel (indirectly and through individual best-responses to population decisions) along the network to distant indirect contacts.

[6] Both the complete graph and the circle are examples of regular networks where all agents have the same number of direct contacts and, thus, hold symmetric positions in the network. By contrast, in the star, agents hold very asymmetric positions, as one agents has $n-1$ direct links while all the other agents only have 1 direct link.

worker). Nash equilibria are thus characterized by the subset S of active criminals and the corresponding crime effort levels; all remaining agents in $N \backslash S$ are workers. The network induced by the initial graph on S and connecting active criminals is unambiguously defined. Given that different subsets S are, in general, interrelated through induced graphs of different geometry, multiple network configurations and crime patterns can emerge at equilibrium for the same conditions on parameter values. Nash equilibria may differ in the actual number of active criminals, the crime-effort level they are providing and/or the geometric pattern of links among them. We also show with an example that delinquents provide a higher individual crime effort when linked to other criminals than not. This is in accordance with the empirical findings of Thornberry *et al.* (2003) who show that networks of criminals or gangs amplify delinquent behaviors

In order to obtain closed-form solutions for the equilibrium crime effort levels, the number of active criminals and the patterns of links connecting them, we focus on *regular networks,* i.e. networks for which each agent has the same number of direct links. Starting from a given network, we look exclusively at the induced *regular* subgraphs that are sustainable at the Nash equilibrium. When criminals are connected through a regular network, they all exert the same crime-effort level which can now be simply expressed in terms of the number of active criminals and the size of the actual network connecting them. Unfortunately, when we restrict to this particular family of networks, existence of equilibrium outcomes is no longer guaranteed. The difficulty is mostly a graph-theoretical issue. For example, start with a star-shaped network with $n = 4$ (i.e. the individual in the center has 3 links and all the other peripheral individuals have only one link). Then, it should be clear that there will never exist an induced regular graph with two links. The only possible induced regular graph is with one link in which two individuals are linked together (the individual in the center linked with any other peripheral individual) and are thus criminals, and the two other individuals are not linked together and can be either criminal or not. Complete graphs are of particular interest when dealing with regular graphs. Indeed, complete networks have the interesting property that all their induced subgraphs are regular, and existence of symmetric Nash equilibria on regular subgraphs is no longer an issue.[7] We show in this case that the aggregate crime level decreases non-linearly with the level of punishment. Moreover, the marginal decrease in aggregate crime level resulting from a marginal increase in punishment intensity increases with the initial value of the punishment. In words, variations of the same size of the punishment level are more effective the higher the statu quo value for such punishment level.

One of the main result of this first analysis is that *ex ante identical individuals connected through a network can end up with very different equilibrium outcomes: either employed, or isolated criminal or criminals in networks.* Part of this ex post heterogeneity is amenable to the presence of geometric asymmetries in the locations held by individuals in the original network (some being initially very well-connected, some not). But, besides this structural network asymmetry across individuals, ex post heterogeneity is also explained by the graph theoretical restrictions on the shape of the induced graphs imposed by the geometry of the original graph.[8] Given the prominent role played by the original network of contacts in shaping individual incentives and equilibrium outcomes, we should expect the agents to try and manipulate the network geometry at their advantage. In particular, one may wonder whether the multiplicity of Nash equilibria is not an artifact driven by the exogenously given initial network of contacts and its particular geometry. In the second part of the paper, we explicitly deal with the issue of endogenous network formation.

A recent literature provides a number of models of network formation. Here, we consider a two-stage network formation and crime decisions game. At the second stage, agents play the crime decisions game

[7]In fact, the graph induced on a set S by the complete graph on the original population N is the complete graph on S.

[8]That may arise even when the original graph is regular, as in the example with $n = 4$ agents on a circle.

described above. At the first stage, we consider the following non-cooperative game of network formation: individuals choose simultaneously with whom they wish to form links.[9] Given the agents wills, we impose that mutual consent is needed for a link to be effectively formed. To rule out coordination problems that plague most games of network formation, we focus on Nash equilibria of the first-stage game with the added requirement that any mutually beneficial link be formed at equilibrium. Therefore, agents decide to form networks in the first stage anticipating their criminal/work decisions that are taken in the second stage.

The multiplicity of Nash equilibria of the second-stage game challenges a general analysis. We thus focus on the case with $n = 4$ agents, for which we provide a whole characterization of the Subgame perfect Nash equilibria (with the refinement mentioned above). We show that only six different network configurations (out of 75) may be sustained at equilibrium of the network formation and crime decision game.[10] In particular, any number of criminals can be obtained at equilibrium depending on the values of w and ϕ. But, given a number of active criminals, strong geometric restrictions are imposed on the network arrangement connecting them. For instance, when only two criminals are active, they are necessarily linked; with three criminals, necessarily one is completely isolated while the remaining two criminals are linked to each other. Because of this feature, the aggregate crime level varies non-linearly with the punishment cost ϕ (holding the wage constant). Transitions from one equilibrium network configuration to another as ϕ varies translate into abrupt variations of this aggregate crime level. Although the network is now a manipulated device, the restrictions on network geometries at equilibrium do not rule out multiplicities of crime patterns. Indeed, for low values of ϕ and/or w, all four criminals are active, but they may interrelated in two different ways: either through the complete graph; else, one agent is isolated and the three others linked through a star.

2 The model

Individual payoffs There are n agents in a set $N = \{1, \ldots, n\}$. All agents are risk-neutral and maximize expected material payoffs. Agents may either be criminals or participate in the labor force. Agents in the labor force earn a wage w, while those involved in criminal activities receive an expected payoff $d_i = p_i (y_i - f) + (1 - p_i) y_i = y_i - p_i f$, where y_i is i's booty, p_i his probability to be caught and f the corresponding fine. Agent i's expected payoffs are thus $\pi_i = \max \{y_i - p_i f; w\}$. The rewards from becoming a criminal are thus balanced against the gains from participating in the labor force.[11]

In our model, criminals also decide how much effort $e_i \in [0, \overline{e}]$ they devote to delinquent behavior. By convention, $e_i = 0$ means that agent i rejects being a criminal and, instead, enters the labor force. Denote by $e = (e_1, \ldots, e_n)$ a population crime effort profile and by e_{-i} the crime efforts profile of all agents in N except agent i. When i is indeed a criminal, we assume that his booty y_i is a function of e, with $\partial y_i (e) / \partial e_i \geq 0$ and $\partial y_i (e) / \partial e_{-i} \leq 0$ (for the component-wise ordering for e_{-i}). In words, individual booties increase with one's involvement in crime (captured by e_i) but decrease with other's involvement in delinquent behavior (captured by e_{-i}), reflecting rivalry in the individual crime gross payoffs.

[9] To this purpose, they simply elaborate a list with the names of the agents they would like to be linked with.

[10] This number corresponds to the case where neither criminal nor worker's identity matter.

[11] Because our model is quite complex, the labor market is kept as simple as possible. However, friends provide information not only on crime but also on job opportunities. The interaction between these two networks (crime and labor market) is certainly an important feature of crime decisions since delinquents have in general few employed friends who can provide information about jobs. The issue is investigated in Calvó-Armengol *et al.* (2003) in a context of much simplier networks in which individuals only belong to mutually exclusive two-person groups (dyads).

The network Besides from being competitors in the crime market, criminals may also benefit from having criminal mates. This benefit may take the form of know-how sharing about delinquent behavior between individuals that know each other. We represent social connections by a graph g, where $g_{ij} = 1$ if i knows j and $g_{ij} = 0$ otherwise. Links are taken to be reciprocal, so that $g_{ij} = g_{ji}$. By convention, $g_{ii} = 0$. Therefore, i and j share their knowledge about delinquent activities if and only if $g_{ij} = 1$.

We assume that a higher individual know-how induces a lower individual probability p_i to be caught when involved in delinquent activities. Know-how is collected from criminal mates. It increases with the number of such mates and with their involvement in crime. Formally, given a network g and a criminal profile e, $\partial p_i(e)/\partial e_j \leq 0$ whenever $g_{ij} = 1$. We also assume that $\partial p_i(e)/\partial e_i \geq 0$, that is, the probability to be caught increases with exposure to crime.

Network payoffs Given a network g, a crime profile e, a fine f and a wage w, the individual expected gains from becoming a criminal are $d_i(e, f, g) = y_i(e) - p_i(e, g) f$, and the overall individual expected payoffs are $\pi_i(e, w, f, g) = \max\{d_i(e, f, g); w\}$. For sake of tractability, we restrict to the following linear expressions for, respectively, the booty and the punishment probability:

$$\begin{cases} y_i(e) = e_i(1 - \sum_{j\in N} e_j) \\ p_i(e, g) = p_0 e_i(1 - \sum_{j\in N} g_{ij} e_j) \end{cases}$$

In the sequel, given a network g, we restrict to those crime profiles e such that both $y_i(e)$ and $p_i(e, g)$ are non-negative, for all $i \in N$. Letting $\phi = p_0 f$ denote the marginal expected punishment cost for an isolated agent, individual expected payoffs become

$$\pi_i(e, w, \phi, g) = \max\{e_i(1 - \sum_{j\in N} e_j) - \phi e_i(1 - \sum_{j\in N} g_{ij} e_j); w\} \tag{1}$$

3 Fixed networks

The crime decision game Consider some given network g connecting individuals. We first assume that g is fixed, and we focus on the individual decisions to become a criminal against entering the labor force. The crime decision game is as follows. The set of players is N, a strategy of player i is a crime effort level $e_i \in [0, \overline{e}]$ for some $\overline{e} > 0$, where $e_i = 0$ means that i enters the labor force and gets the wage w, and payoffs are given by (1).

Note that the individual payoffs of this crime decision game depend both on the strategy profile $(e_1, ..., e_n)$ being played and on the topology of the underlying network connecting individuals. But, given that the network structure influencing payoffs is exclusively the one connecting active criminals among themselves, the actual topology of the network affecting payoffs is itself shaped by the strategies adopted by the players (either work or become a criminal; and, if a criminal, how much effort to devote to such activity). The impact of individual decisions on the criminal network and on payoffs thus goes either ways. This interplay between individual strategies and interaction structure is at the heart of our analysis.[12]

Given a network g, an exogenously given wage w and the marginal expected punishment cost for an isolated individual ϕ, we denote the corresponding crime decision game by $\Gamma(w, \phi, g)$. We solve for the Nash equilibria in pure strategies of this game. These equilibria depend on w, ϕ and g.

[12] For another model where strategies and interaction structure are interrelated and, together, determine individual payoffs in a public good settings, see Bramoullé and Kranton (2003).

Solving for the crime decision game Given a crime decision profile e, agent i's gains from crime are:

$$d_i(e,\phi,g) = e_i(1-\sum_{j\in N} e_j) - \phi e_i(1-\sum_{j\in N} g_{ij}e_j),$$

with cross-derivatives $\partial^2 d_i/\partial e_i \partial e_j = -1+\phi g_{ij}$. We distinguish two cases. First, when $\phi < 1$, the cross-derivatives are always negative and crime effort decisions are strategic substitutes.[13] Second, if $\phi \geq 1$, then $\partial^2 d_i/\partial e_i \partial e_j < 0$ when $g_{ij} = 0$ while $\partial^2 d_i/\partial e_i \partial e_j \geq 0$ when $g_{ij} = 1$. In words, crime decisions are global strategic substitutes but local strategic complements, where local (resp. global) refers to directly linked (resp. not directly linked) individuals. We have the following result.

Lemma 1 *When $\phi \geq 1$, at the unique Nash equilibrium of $\Gamma(w,\phi,g)$, all agents enter the labor force.*

Proof. Suppose that $\phi \geq 1$. We show that $\pi_i(0,e_{-i}) \geq \pi_i(e_i,e_{-i})$, for all $(e_i,e_{-i}) \in [0,\overline{e}]^n$ and $i \in N$. First note that $\pi_i(0,e_{-i}) = \max\{0,w\} = w$, for all e_{-i}. Suppose that $\pi_i(\widetilde{e}_i,\widetilde{e}_{-i}) > w$ for some $\widetilde{e}$ and $i \in N$. Then, $d_i(\widetilde{e},\phi,g) > w$. Given that both $(1-\phi) \leq 0$ and $-\phi\sum_{j\in N}(1-g_{ij})e_j \leq 0$, necessarily both $e_i > 0$ and $1-\sum_{j\in N} e_j < 0$, implying that $y_i(\widetilde{e}) < 0$. ∎

From now on we restrict to the case $\phi < 1$.

Consider some w, ϕ and g. We describe a simple procedure to construct the Nash equilibria in pure strategies of $\Gamma(w,\phi,g)$. To this purpose, we introduce an auxiliary game, denoted $\Gamma^*(\phi,g)$, and defined as follows. Players in N select an effort level $e_i \in \mathbb{R}$ and agent i's payoffs are $d_i(e,\phi,g)$. In other words, $\Gamma^*(\phi,g) = \Gamma(-\infty,\phi,g)$ with the added requirement that the individual strategy set is now $\mathbb{R}$ instead of $[0,\overline{e}]$.

Lemma 2 *There exists a finite set $\mathcal{Z} \in \mathbb{R}$ such that, for all $\phi \in (0,1)\backslash\mathcal{Z}$ and all network g on N, the set of Nash equilibria in pure strategies of $\Gamma^*(\phi,g)$ exists and is unique.*

We refer to the situations in which $\phi \notin \mathcal{Z}$ as generic situations. Since $\mathcal{Z}$ is a finite set, the whole set of nongeneric situations has Lebesgue measure of zero. For the equilibrium analysis, we restrict from now on to generic situations.

For all ϕ and g, denote by $e^*(\phi,g) = (e_1^*(\phi,g),\ldots,e_n^*(\phi,g)) \in \mathbb{R}^n$ the unique Nash equilibrium in pure strategies of $\Gamma^*(\phi,g)$. This equilibrium is obtained from the following (standard) procedure. First, given some profile $e \in \mathbb{R}^n$, we derive the best-response function of each agent $i \in N$, $BR_i(e_{-i})$, from the first-order condition on $d_i(e,\phi,g)$. Then, the n equations $BR_i(e_{-i}) = e_i$, $i \in N$ characterizing the equilibrium efforts of $\Gamma^*(\phi,g)$ define a linear system of n equations:

$$2e_i + \sum_{j\neq i}(1-\phi g_{ij})e_j = 1-\phi, i \in N \tag{2}$$

with n unknowns e_i, whose unique solution is precisely $e^*(\phi,g)$.[14]

Consider some wage level w, marginal punishment cost ϕ and network g on N. We first introduce a definition.

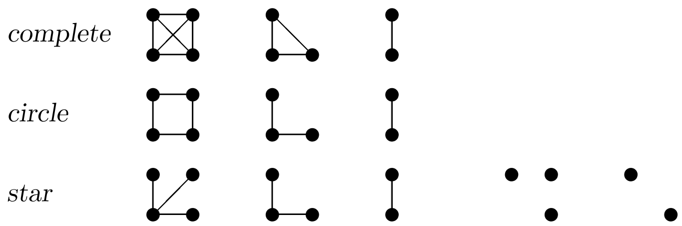
[13] Strictly speaking, crime efforts are strategic substitutes insofar we ignore the outside opportunity to enter the labor force or, equivalently, we set $w=-\infty$.

[14] Note that payoffs in $\Gamma^*(\phi,g)$ satisfy all the required smoothness conditions for all the Nash equilibria of the game to be exactly characterized by this set of equations.

Definition 1 *For all subset $S \subset N$ of players in N, let $g(S)$ such that $g_{ij}(S) = 1$ if and only if both $g_{ij} = 1$ and $i, j \in S$.*

We say that $g(S)$ is the network induced by g on S. The network $g(S)$ is obtained the following way. Originally, all agents in N are connected according to some given network g. Prominent examples of such networks are (a) the complete graph, where each agent is directly linked to every other agent in the population, (b) the star-shaped graph, where some given agent, say agent 1, is related to every other agent in the population, while every other agent only has agent 1 as his direct contact, (c) a circle, where each agent has exactly two direct contacts. Suppose now that we shrink the population from N to $N \backslash \{i\}$. This has an impact on the geometry of the links among the remaining set of player $N \backslash \{i\}$. Indeed, by eliminating agent i from the population, we also eliminate all the direct links stemming from i in the original graph g. The network we obtain after eliminating i's node and corresponding direct links is denoted $g(N \backslash \{i\})$ and termed network induced on $N \backslash \{i\}$ by g. Suppose now we want to obtain the subnetwork $g(S)$ of g induced by some originally given network g on some subset S of agents. Consider the set $N \backslash S$ of agents not in S. Then, we simply eliminate from g every node corresponding to an agent in $N \backslash S$ and every direct link stemming from those agents. The resulting network is $g(S)$.

The figure below shows the possible network geometries obtained from the complete graph, a star-shaped graph and a circle for $n = 4$ when we remove progressively one node from the population (and its corresponding direct links). We omit the cases with one isolated node alone.



As we remove nodes from either the complete graph or the circle, we obtain a nested chain of induced (sub)networks. The case of the star is a bit different as we get two chains of nested induced (sub)graphs. One chain is obtained by removing progressively the peripheral players; the other chain is obtained by first removing the central player and then the peripheral players. In the first case, induced subgraphs are themselves stars with a fewer number of peripheral players. In the second case, induced subgraphs consist on isolated players, as all the links in the original network g stem from the central player being removed first. The precise identities of the agents being removed (and not only their number) thus may considerably impact the shape of the resulting induced graphs. The complete graph is a remarkable exception as, in this case, only the number of agents being removed (and not their precise labeling) matters.

As the previous examples show, the geometry of the original graph imposes restrictions on the possible geometries for the induced subgraphs. In general, the set of subgraphs for different original graphs do not coincide.[15] Both these restrictions on subgraphs and the dependence of the shape of the subgraphs on the identity of the agents being removed (and not only their number) will be at the root of both the multiplicity of the equilibria of the game and some equilibrium existence problems. We discuss these issues below. We first characterize the Nash equilibria of the crime decisions game.

[15] Yet, two identical subgraphs may sometimes be obtained from different original graphs (as for the star with two peripheral agents obtained both from the star and the circle).

The procedure to obtain the Nash equilibria of $\Gamma(w, \phi, g)$ builds on the computation of the Nash equilibria of the auxiliary game $\Gamma^*(\phi, g)$ (where the outside option provided by the labor market has been removed) on all the possible subgraphs $g(S) \subset g$ induced by the original network g on all possible subsets $S \subset N$ of players. With this list of equilibrium effort levels in hand for all the $g(S)$, $S \subset N$, and given some wage level w, it is easy to single out those subsets S of criminals and corresponding equilibrium profiles of the auxiliary game for which no criminal in S has incentives to take the outside option w, and no worker in $N \backslash S$ has incentives to enter the crime pool.

More precisely, for all $S \subset N$, compute the unique Nash equilibrium in pure strategies of $\Gamma^*(\phi, g(S))$, that we denote by $e^*(\phi, g(S))$. As seen before, this amounts to solving a linear system of n equations with n unknowns. Define:

$$\begin{cases} \overline{m}(\phi, S) = \min\{e_i^*(\phi, g(S)) \mid i \in S\}, \text{ for all } S \subset N \\ \underline{m}(\phi, S) = \max\{e_j^*(\phi, g(S \cup \{j\})) \mid j \notin S\}, \text{ for all } S \subset N, S \neq N \\ \underline{m}(\phi, N) = 0 \end{cases}$$

Then, we have:

Proposition 1 *Let $S \subset N$. If $\overline{m}(\phi, S) > \underline{m}(\phi, S) \geq 0$, then the crime decision profile e such that $e_i = e_i^*(\phi, g(S))$ for all $i \in S$, and $e_i = 0$ otherwise is a Nash equilibrium of $\Gamma(w, \phi, g)$ for all wage w such that $\overline{m}(\phi, S) > \sqrt{w} > \underline{m}(\phi, S)$. Moreover, all the Nash equilibria of $\Gamma(w, \phi, g)$ are of this sort.*

The intuition for the wage range condition is as follows. First, note that for all ϕ and g, the equilibrium payoffs of the subsidiary game $\Gamma^*(\phi, g)$ are exactly $d_i(e_i^*(\phi, g)) = [e_i^*(\phi, g)]^2$, that is, equilibrium payoffs coincide with the square of equilibrium effort levels. Consider now the crime decision game $\Gamma(w, \phi, g)$. At any equilibrium of $\Gamma(w, \phi, g)$ involving exactly a set S of criminals, no worker in $N \backslash S$ gains by entering the crime business (that is, $w > [\underline{m}(\phi, S)]^2$) and no worker in S gains by participating in the labor force (that is, $[\overline{m}(\phi, S)]^2 > w$). Stating the condition with $\sqrt{w}$ instead of w has the added virtue to check for positive crime effort levels at equilibrium.

When $\overline{m}(\phi, S) > \sqrt{w} > \underline{m}(\phi, S)$ for some w and S, at all the Nash equilibria of $\Gamma(w, \phi, g)$, there are exactly $|S|$ criminals and $n - |S|$ workers. At every such equilibria, $g(S)$ is the know-how sharing network connecting active criminals. Links in $g \backslash g(S)$ connect workers to workers or workers to criminals. Therefore, no actual know-how is being shared between the end nodes of such connections, and links in $g \backslash g(S)$ are redundant at equilibrium.

Proposition 1 does not establish uniqueness of the Nash equilibria for every set of the parameter values w, ϕ and g. In fact, as illustrated below with an example, different crime patterns corresponding to different subsets S and S' of active criminals can be sustained at equilibrium for the same parameter values. The multiplicity arises from the fact that, for some networks g, two different networks of active criminals $g(S)$ and $g(S')$, $g(S) \neq g(S')$, can arise at equilibrium for identical w and ϕ.

Existence of Nash equilibria in pure strategies of $\Gamma(w, \phi, g)$ is a side-product of the previous characterization result.

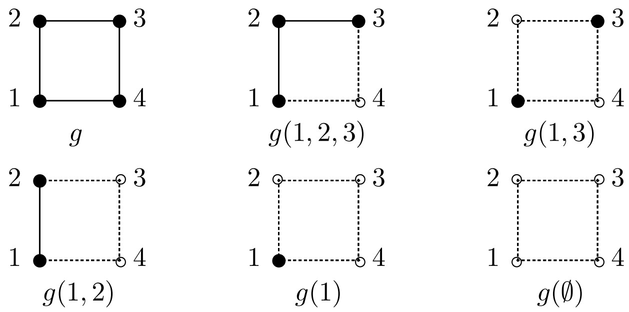
Corollary 1 *For all w, ϕ and g, the crime decision game $\Gamma(w, \phi, g)$ has a pure strategy Nash equilibrium.*

Proof. If there exists some $S \subset N$ such that $\overline{m}(\phi, S) > \underline{m}(\phi, S) \geq 0$, then Proposition 1 applies. Otherwise, all agents working is a Nash equilibrium. ∎

We now work out all the Nash equilibria in an example with $n = 4$ agents located on a circle g. We show that, under certain conditions on w and ϕ, multiple criminal networks can arise at equilibrium for the same parameter values. The example also serves the purpose to illustrate the differential effects of the competition for the booty and the know-how sharing among direct mates on equilibrium outcomes.

Example with $n = 4$ agents on a circle Consider $n = 4$ agents arranged on a circle g where each agent has exactly two direct contacts. The network connecting agents is represented by a graph where nodes stem for agents and arcs represent direct social links between their end nodes. We follow the convention to represent criminals (resp. workers) with full (resp. empty) nodes. As no actual crime knowledge is shared among workers, or between a worker and a criminal, the arcs stemming from workers are represented by dashed lines (they are redundant).

Fix $\phi \in (0, 1)$. Then, any of the crime pattern depicted below can be sustained as a Nash equilibrium for a suitable wage range.[16]



More precisely, let $N = \{1, 2, 3, 4\}$. For all subset $S \subset N$ of agents, let $e^* (g (S))$ denote the Nash equilibrium profile where only agents in S are criminals, while agents in $N\backslash S$ are workers. The network connecting criminals is then $g (S)$, that is, the network induced by g on S. Specializing and solving the equilibrium equations (2) of $\Gamma^* (\phi, g')$ for all induced network $g' \subset g$, we obtain the following equilibrium effort levels:

Network g'	g	$g(1,2,3)$	$g(1,3)$	$g(1,2)$	$g(1)$	$g(\emptyset)$
$e_1^* (\phi, g')$	$\frac{1-\phi}{5-2\phi}$	$\frac{1-\phi^2}{4+4\phi-2\phi^2}$	$\frac{1-\phi}{3}$	$\frac{1-\phi}{3-\phi}$	$\frac{1-\phi}{2}$	0
$e_2^* (\phi, g')$	$\frac{1-\phi}{5-2\phi}$	$\frac{(1+2\phi)(1-\phi)}{4+4\phi-2\phi^2}$	0	$\frac{1-\phi}{3-\phi}$	0	0
$e_3^* (\phi, g')$	$\frac{1-\phi}{5-2\phi}$	$\frac{1-\phi^2}{4+4\phi-2\phi^2}$	$\frac{1-\phi}{3}$	0	0	0
$e_4^* (\phi, g')$	$\frac{1-\phi}{5-2\phi}$	0	0	0	0	0

We have the following inequalities:

$$\begin{cases} e_1^* (g(1)) > e_1^* (g(1,2)) > e_1^* (g(1,3)) > e_2^* (g(1,2,3)) > e_1^* (g(1,2,3)) > e_1^* (g), \text{ if } 0 < \phi < \widetilde{\phi} \\ e_1^* (g(1)) > e_1^* (g(1,2)) > e_2^* (g(1,2,3)) > e_1^* (g(1,3)) > e_1^* (g(1,2,3)) > e_1^* (g), \text{ if } \widetilde{\phi} < \phi < 1 \end{cases}$$

for some uniquely defined $\widetilde{\phi} \in (0, 1)$. From these inequalities, we deduce the following:

Equilibrium network	g	$g(1,2,3)$	$g(1,3)$	$g(1,2)$	$g(1)$	$g(\emptyset)$
Upper bound for $\sqrt{w}$	$\frac{1-\phi}{5-2\phi}$	$\frac{1-\phi^2}{4+4\phi-2\phi^2}$	$\frac{1-\phi}{3}$	$\frac{1-\phi}{3-\phi}$	$\frac{1-\phi}{2}$	$+\infty$
Lower bound for $\sqrt{w}$	0	$\frac{1-\phi}{5-2\phi}$	$\frac{(1+2\phi)(1-\phi)}{4+4\phi-2\phi^2}$	$\frac{1-\phi^2}{4+4\phi-2\phi^2}$	$\frac{1-\phi}{3-\phi}$	$\frac{1-\phi}{2}$

[16]See the appendix for more details. In fact, $g(1,3)$ can only emerge at equilibrium under some conditions both on w and on ϕ, as we discuss below.

The following comments are in order. First, for those S such that $i \in S$, $e_i^*(g(S))$ increases with $|S|$, reflecting the competition or over-crowding effect on the booty size $y_i(e)$. Second, $e_1^*(g(1,2)) > e_1^*(g(1,3))$. There are exactly two agents involved in delinquent behavior both in $g(1,2)$ and in $g(1,3)$. Only in $g(1,2)$, though, do the active criminals effectively share their knowledge. The inequality then simply reflects the positive effect of actual knowledge on the level of crime. Third, $e_2^*(g(1,2,3)) > e_1^*(g(1,3))$ if and only if $\phi > \widetilde{\phi}$. Despite there being more criminals in $g(1,2,3)$ than in $g(1,2)$, when the premium to sharing knowledge (as captured by ϕ) is high enough, the knowledge sharing positive effect on crime efforts overwhelms the competitive negative effect on crime involvement.[17]

Finally, when $\phi < \widetilde{\phi}$, both $g(1,2)$ and $g(1,3)$ can be sustained at equilibrium for the (non-empty) wage range $e_1^*(g(1,3)) > \sqrt{w} > e_2^*(g(1,2,3))$. Consider for instance $g(1,2)$. Given that $e_1^*(g(1,2)) > e_1^*(g(1,3)) > \sqrt{w}$, no criminal in $g(1,2)$ (that is, neither agent 1 nor agent 2) gains by entering the labor force. Moreover, given that $\sqrt{w} > e_2^*(g(1,2,3)) > e_1^*(g(1,2,3))$, no worker in $g(1,2)$ (that is, neither agent 3 nor agent 4) gains by dropping out from the labor market and becoming a criminal. Therefore, no unilateral deviation from $g(1,2)$ is profitable for neither type of agents (nor criminals, nor workers). The same reasoning applies to $g(1,3)$. It is readily checked that, whenever $g(1,2)$ and $g(1,3)$ coexist at equilibria, the actual payoff allocation corresponding to $g(1,2)$ Pareto dominates that from $g(1,3)$ because of the positive effect of sharing knowledge in $g(1,2)$, absent in $g(1,3)$.

Regular networks In order to obtain closed-form solutions, we now focus on general regular networks. Regular networks are such that $\sum_{l \in N} g_{il} = \sum_{l \in N} g_{jl} = k$, for all $i, j \in N$. In a regular network, all agents have the same number of direct contacts k that we refer to as the degree of g. A regular network g of degree k is denoted by g_k. For instance, the complete graph on a population of n agents is a regular network of size $n-1$ and may well be denoted by g_{n-1}. Also, the circle is a regular network of size 2 that we denote g_2.

The previous example shows all the possible Nash equilibrium patterns when $n = 4$ and agents are originally arranged on a circle. Some of these Nash equilibria involve criminals connected through a regular network, as in g where all active criminals are connected to exactly two other active criminals, in $g(1,2)$ where the two active criminals are in touch with each other. In some other cases, criminals are isolated, as in $g(1,3)$ or in $g(1)$ or hold asymmetric positions in the network of know-how sharing, as in $g(1,2,3)$, where agent 2 is in contact with two criminals whereas both 1 and 3 are only linked to one criminal each.

The following result provides a general characterization of the Nash equilibria of the crime decisions game whereby criminals, at equilibrium, are connected through a regular network.

Proposition 2 *At every Nash equilibrium of $\Gamma(w, \phi, g)$ involving exactly a set S of criminals connected through a regular network $g(S) = g_k$, the equilibrium crime effort levels are $e_i^*(\phi, g(S)) = (1-\phi)/(|S| + 1 - k\phi)$, for all $i \in S$.*

It is readily checked that, for all $i \in S$, $e_i^*(\phi, g_k(S))$ increases with the degree k of the know-how sharing network, decreases with the number $|S|$ of total criminals (competition effect), and decreases with the punishment cost ϕ (deterrence effect).

The previous characterization result does not guarantee existence of such symmetric Nash equilibria of the crime decision game where criminals are connected through regular networks. Establishing existence is

[17] Note also that $e_2^*(g(1,2,3)) > e_1^*(g(1,2,3))$, reflecting the comparative knowledge advantage of the central agent 2 in $g(1,2,3)$ with respect to the two peripheral agents 1 and 3.

a twofold task. First, given a wage level w, a punishment cost ϕ and a degree k, we need to determine which sets S of criminals, if any, arise at equilibrium.[18] This is a standard *game-theoretical existence problem*. Second, we need to check whether criminals in S are indeed connected though a regular network g_k, where the network g_k is the one induced by g on S. This is a *graph-theoretical existence problem* as it amounts to identifying topological conditions, if any, on the original network g ensuring that $g(S) = g_k$ for the sets S that are candidates to equilibrium. The graph-theoretical existence problem is not trivial. For instance, when $n = 4$ and agents are originally on the circle g_2, when $\sqrt{w} \in \left(\frac{1-\phi}{5-2\phi}; \frac{1-\phi^2}{4+4\phi-2\phi^2}\right)$, all agents in $S = \{1, 2, 3\}$, and only those agents, are prone to become criminals, whereas when $\sqrt{w} \in \left(\frac{1-\phi^2}{4+4\phi-2\phi^2}; \frac{1-\phi}{3-\phi}\right)$ the candidate criminal agents are $S = \{1, 2\}$. In the first case, the network $g(1, 2, 3)$ induced by the original graph on the candidate set of criminals $\{1, 2, 3\}$ is not regular, whereas $g(1, 2)$ is a regular network of size one. We deal with the two existence problems separately.

Fix w, ϕ and k. Suppose first that the network induced on any equilibrium candidate set S of criminals is such that $g(S) = g_k$. Let $s^*(w, \phi, k) = (1-\phi)/\sqrt{w} + k\phi - 1$. To simplify the statement of the following result, we suppose that the size n of the population is such that $n \geq s^*(w, \phi, k)$.

Proposition 3 *If $\sqrt{w} \leq 1/(k+2)$, there exists a Nash equilibrium of $\Gamma(w, \phi, g)$ with exactly $s^*(w, \phi, k)$ criminals connected through a regular network of size k, and $n - s^*(w, \phi, k)$ workers.*

Proof. First note that, when $g(S) = g_k$, $e_i^*(\phi, g(S)) \leq 1/(k+2)$, as there are at least $k+1$ nodes in a regular network of degree k, which explains the condition on $\sqrt{w}$. Second, s^* is defined such that, for all set S^* of criminals where $g(S^*) = g_k$ and $|S^*| = s^*$, we have $e_i^*(\phi, g(S^*)) = \sqrt{w}$. ∎

Strictly speaking, the equilibrium size $s^*(w, \phi, k)$ of the criminals pool is, in fact, equal to the highest integer smaller or equal than $(1-\phi)/\sqrt{w} + k\phi - 1$. The condition $\sqrt{w} \leq 1/(k+2)$ simply guarantees that $s^*(w, \phi, k) > 0$.

Applying the chain rule, it is a simple algebra exercise to check that $\partial e_i^*(\phi, g(S^*))/\partial k \geq 0$ whenever $k \geq 1$.[19] In particular, the aggregate level of crime $\sum_{i \in S} e_i^*$ increases with the degree k of the network connecting criminals. Therefore, criminal interconnections generate a crime level premium with respect to the case with no social interactions among criminals, and this premium increases with the density of the existing pattern of connections among criminals. The social setting and its density or tightness have thus a multiplier effect on aggregate observed crime levels.

Also, one can easily check that $\partial e_i^*(\phi, g(S^*))/\partial \phi = 0$. At equilibrium, both the actual pool size of criminals and the crime effort level of active delinquents adapt endogenously to variations of the crime punishment level in a way that renders such external variations ineffective. In particular, the elasticity of the aggregate level of crime with respect to the deterrence level ϕ is zero.

This observation, though, needs qualifying. Indeed, so far, the degree of the regular network k connecting the S^* criminals at equilibrium is assumed to be exogenous. Yet, the geometry of the initial network g imposes very strong restrictions on the regular subnetworks that can be effectively induced by g on any subset of N.[20] Consider for instance the $4-$agents circle g in the example above, where each agent has exactly two direct contacts. The shape of g clearly imposes many restrictions on the possible regular subnetworks induced by

[18] Assuming that such criminals are connected at equilibrium by a regular network of degree k

[19] Indeed, $\partial\left[s^*(w, \phi, k)\, e_i^*(\phi, g(S^*))\right]/\partial k = (k-\phi)(1-\phi)/(s^*+1-k\phi)^2$.

[20] Recall that, at equilibrium, $g(S^*) = g_k$, that is, the regular network g_k connecting the S^* criminals needs to coincide with the network induced by g on S^*.

g on subsets of $N = \{1, 2, 3, 4\}$. In this example, $g(1,2)$, $g(2,3)$, $g(3,4)$ and $g(4,1)$ are all regular networks of size 1 induced by g on subsets of N. Yet, these are the only subsets of N on which g induces a regular network of size 1. For instance, $g(1,3)$ is regular but of size 0, while $g(1,2,3)$ is not regular as agent 2 has two links while 1 and 3 only one.[21] Suppose that, initially, there are exactly 4 criminals arranged in the regular network g. A (properly calibrated) increase in ϕ induces, at equilibrium, a reduction of the number of active criminals to 3. With three criminals, the corresponding network arrangement $g(1,2,3)$ is no longer a regular network. In this case, the restrictions the particular geometry of the original network g imposes on the attainable induced subnetworks does not allow the set of criminals that remain active (after ϕ has increased) to rearrange themselves into a regular network. In this simple example, the shape of the equilibrium network of criminals can not adapt endogenously, together with the crime pool, to the increase of ϕ so as to render this increase ineffective, and the elasticity of the aggregate crime level to an increase in ϕ is not zero.

The existence of a regular subnetwork g_k on the equilibrium set S^* of criminals induced by some initially given network g on S^* is essentially a graph theoretical issue that we shall not contemplate here. We will rather focus on a particular class of networks where the problem of existence is trivially solved.

Suppose that the initial network connecting agents is the complete graph $\overline{g}$ on N where every agent is directly linked to every other agent, that is, $\overline{g}_{ij} = 1$, for all $i \neq j$. In $\overline{g}$, each agent has exactly $n-1$ connections. Then, for each subset $S \subset N$, the network $\overline{g}(S)$ induced by $\overline{g}$ on S is also a complete graph on S where each agent in S is directly linked to every other agent in S. In $\overline{g}(S)$, all agents in S have exactly $|S| - 1$ links (while those in $N \backslash S$ have no links). In words, all networks induced on a subset S by the complete network are complete networks on the corresponding subset S. A previous example with $n = 4$ illustrates this particular property of complete graphs.

Fix w and ϕ. Let $\overline{s}(w, \phi) = 1/\sqrt{w} - (1+\phi)/(1-\phi)$ and, for simplicity, assume that $n \geq \overline{s}(w, \phi)$.

Corollary 2 *Suppose that initially all agents are linked through the complete network $\overline{g}$. Then , if $\sqrt{w} \leq (1-\phi)/(1+\phi)$, there exists a Nash equilibrium of $\Gamma(w, \phi, \overline{g})$ with exactly $\overline{s}(w, \phi)$ criminals fully interconnected and $n - \overline{s}(w, \phi)$ workers.*

At any such equilibria, active criminals exert a crime effort $\overline{e}(w, \phi) = (1-\phi)/[1+\phi+\overline{s}(w,\phi)(1-\phi)]$. It is readily checked that the elasticity $\eta_{\overline{se},\phi}$ of the aggregate crime rate $\overline{se}(w, \phi)$ with respect to the punishment level ϕ is negative and increasing in absolute terms.[22] Therefore, the marginal impact on aggregate crime (measured through the resulting decrease of such aggregate crime level) of an increase $\Delta\phi$ in the punishment level is highly non-linear and increases with the initial value for ϕ.

4 Endogenous networks

We should expect criminals to select strategies both to maximize the size of their booty and to minimize the individual probability to be caught. In this section, we consider the endogenous formation of networks so as to encompass both dimensions of strategic behavior.

[21] Recall that we are considering so far the case of fixed networks, where agents can neither cut existing links nor add new connections. Therefore, knowledge is effectively shared between two initially directly connected agents that end up being criminals at equilibrium.

[22] We have $\partial\overline{se}/\partial\phi = -2/\left[1-\phi^2+\overline{s}(1-\phi)^2\right] < 0$ and $\partial^2\overline{se}/\partial\phi^2 = -4\left[1+\phi+\overline{s}(1-\phi)\right]/\left[1-\phi^2+\overline{s}(1-\phi)^2\right]^2 < 0$.

A recent literature provides a number of models of network formation, together with appropriate equilibrium concepts.[23] We first describe the non-cooperative game of network formation that we adopt for our analysis. We then describe the two-stage game of network formation and crime decision that we analyze.

A non-cooperative network formation game with mutual consent[24] Consider some payoff function $u(g) = (u_1(g), \ldots, u_n(g))$ that assigns a payoff to every agent in N as a function of the underlying network g connecting such agents. For each such payoff function u, consider the following network formation game.

The set of players is N. Agents in N individually announce all the links they wish to form. For all $i, j \in N$, $\omega_{i,j} = 1$ if i wants to link with j, and $\omega_{i,j} = 0$ otherwise. By convention, $\omega_{i,i} = 0$. A strategy of agent i is $\omega_i = (\omega_{i,1}, \ldots, \omega_{i,n})$, and $\Omega^i = \{0,1\}^{n-1}$ is the set of strategies available to i. The link ij is created if and only if $\omega_{i,j}\omega_{j,i} = 1$. Links are thus created only by mutual consent. A strategy profile $\omega = (\omega_1, \ldots, \omega_n)$ induces a non-directed graph $g(\omega)$ and a vector of payoffs $u(g(\omega))$. We omit ω in the sequel when no confusion is possible.

We denote this network formation game by $\Psi(u)$.

Pairwise-equilibrium networks A strategy profile $\omega^* = (\omega_1^*, \ldots, \omega_n^*)$ is a Nash equilibrium of the network formation game $\Psi(u)$ if and only if $u_i\left(g\left(\omega_i^*, \omega_{-i}^*\right)\right) \geq u_i\left(g\left(\omega_i, \omega_{-i}^*\right)\right)$, for all $\omega_i \in \Omega^i$. Following Goyal and Joshi (2002), we refine Nash equilibrium building upon the pairwise stability concept in Jackson and Wolinsky (1996). We require that any mutually beneficial link be formed at equilibrium. We refer to such particular class of Nash equilibria as *pairwise-equilibrium networks*.

Definition 2 *g is a pairwise-equilibrium network of $\Psi(u)$ if and only if there is a Nash equilibrium strategy profile which supports g and, for all $ij \notin g$, if $u_i(g+ij) \geq u_i(g)$, then $u_j(g) > u_j(g+ij)$.*

Therefore, g is a pairwise-equilibrium network of $\Psi(u)$ if and only if no player gains by cutting any of the existing link, and no two players not yet connected both gain by creating a direct link to each other.

The two-stage game of network formation and crime decision Consider now the following two-stage game of network formation. In the first stage, agents decide non-cooperatively with whom they wish to form links to share their know-how with. We model this stage as a network formation game with mutual consent, as described above. In the second stage, individual decisions to become a criminal or to enter the labor market are taken simultaneously. Here, we consider the game analyzed in the previous section.[25]

[23] See, for instance, Jackson and Wolinsky (1996) and Bala and Goyal (2000) for seminal contributions, and Jackson (2003) for a survey of recent work in this flourishing new strand of research. Ioannides and Datcher Loury (2002) survey the network literature from the particular prism of information exchange networks.

[24] A similar non-cooperative game and equilibrium concept to model network formation in different contexts has been used, for instance, in Calvó-Armengol (2003) and Goyal and Joshi (2002).

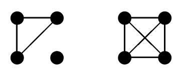
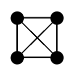
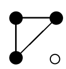
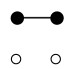
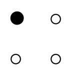
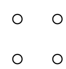
[25] A link between two criminals has both a positive and a negative effect on the newly linked agents. First, because it provides access to know-how about criminal behavior, it decreases the probability to be caught, which is a benefit. Second, because the newly linked partner also benefits from the know-how being shared, the competition for the booty exerted by such partner increases, which is a cost. Given this effects of both signs, we assume that establishing a link is costless, the cost being indirectly induced by the know-how transmitted to the new partner. For another model of network formation with indirect costs for establishing links, see the co-author model in Jackson and Wolinsky (1996).

We denote this two-stage game by $(\Psi \circ \Gamma)(w, \phi)$. We consider a refinement of subgame perfect Nash equilibria (SPNE) of this game as we focus on pairwise-equilibrium networks for the first-stage game. We refer to such SPNE as *pairwise-SPNE*.

We solve the game backwards. At the second stage, agents play the crime decision game $\Gamma(w, \phi, g)$. We denote by $\pi^*(w, \phi, g)$ the Nash equilibrium outcomes of such game that assigns a payoff to each agent in N for each network g.[26] At the first stage, agents play the network formation game $\Psi(\pi^*(w, \phi, \cdot))$. The potential multiplicity of Nash equilibrium outcomes for the second-stage crime decision game challenges a full-fledged equilibrium analysis of the two-stage game of network formation and crime decision. We thus focus on the particular case of $n = 4$ agents.[27]

An example with $n = 4$ agents We show that only six different network configurations can be sustained as pairwise-SPNE of $\Psi \circ \Gamma$.[28]

Proposition 4 *When $n = 4$, and up to a relabelling of players, the only pairwise-SPNE networks characterized by $\overline{m} > \sqrt{w} \geq \underline{m}$ are the following:*

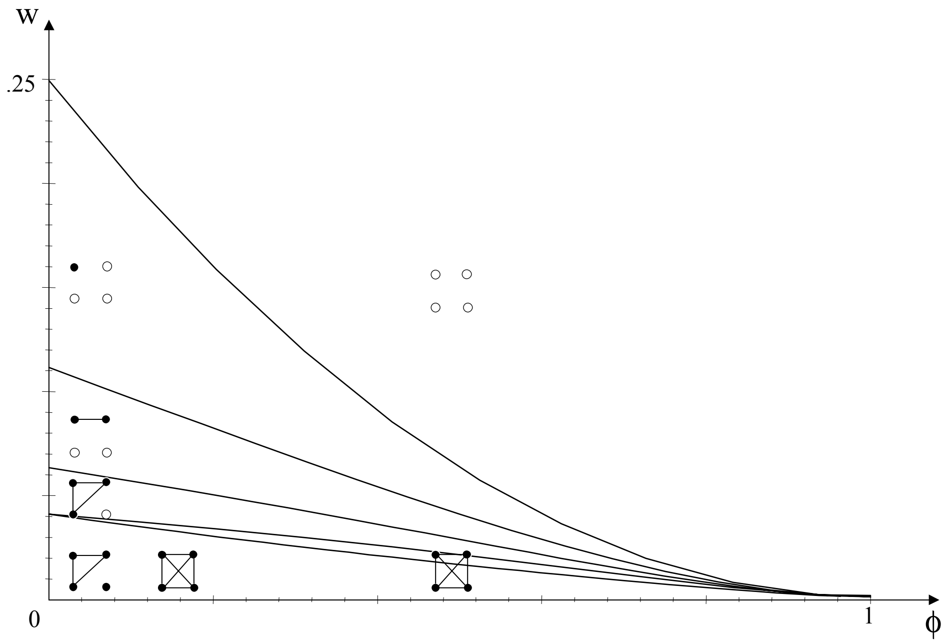
						
$\overline{m}$	$\frac{(1-\phi)(2-\phi)}{10-8\phi}$	$\frac{1-\phi}{5-3\phi}$	$\frac{1-\phi}{4-2\phi}$	$\frac{1-\phi}{3-\phi}$	$\frac{1-\phi}{2}$	$+\infty$
$\underline{m}$	0	$\frac{(1-\phi)(2-\phi)}{10-8\phi}$	$\frac{1-\phi}{5-3\phi}$	$\frac{1-\phi}{4-2\phi}$	$\frac{1-\phi}{3-\phi}$	$\frac{1-\phi}{2}$

These equilibrium configurations are depicted below as a function of w and ϕ.

[26]Recall that, in the previous section, we have characterized the Nash equilibrium outcomes of this second-stage game $\Gamma(w, \phi, g)$ for any given fixed network g.

[27]Note also that, given a set $N = \{1, \dots, n\}$ of agents, there exist $\sum_{k=1}^{n} 2^{\frac{k(k-1)}{2}}$ different network configurations among all the possible subsets of criminals in N, up to a relabelling of agents (if criminals' identity matters, this number increases up to $\sum_{k=1}^{n} \binom{n}{k} 2^{\frac{k(k-1)}{2}}$). For instance, when $n = 4$, there are 75 network configurations of criminals to be considered (if criminals' identity matters, there are 112 such configurations).

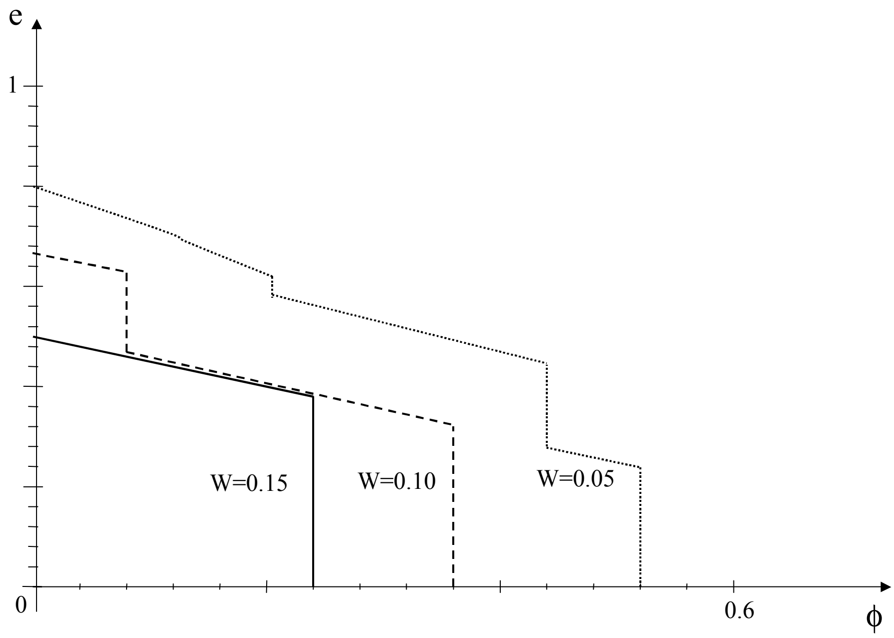
[28]See the appendix for more details.



Any number of criminals can be obtained at equilibrium depending on the actual values of w and ϕ. The equilibrium number of criminals decreases with w (holding ϕ constant) and with ϕ (holding w constant). At equilibrium, for any given number of active criminals, strong geometric restrictions are imposed on the actual know-how sharing network among these criminals. For instance, whenever only two agents are criminals at equilibrium, both criminals agree to link each other at equilibrium. With three criminals, the equilibrium network is asymmetric as two criminals form a pair while the third one remains isolated. Finally, with four criminals, two different situations may arise. One in which every criminal is in direct contact with every other criminal in the population (links form a complete network); one in which one criminal is alone, and the three remaining criminals are all directly linked to each other.

Given a value for the exogenous parameters w and ϕ, the equilibrium aggregate level of crime defined as $e^* = e_1^* + ... + e_4^*$ depends both on the number of active criminal and on the actual (equilibrium) network connecting them. Given that the network of links is endogenously determined, and that network equilibrium configurations differ drastically from one another (in terms of their geometry) variations of ϕ (while holding w constant) yield abrupt variations on e^* that reflect the transition from one network configuration to another. The following figure shows the aggregate level of crime as a function of ϕ for different values of w

and illustrates the step-shape of $e^* (\phi)$.



Besides this non-linear variation of the aggregate crime rate with respect to the punishment level ϕ, a salient feature of the game of network formation and crime decision $\Psi \circ \Gamma$ is the potential multiplicity of equilibrium outcomes. With $n = 4$ agents, two different network configurations with 4 active criminals can be sustained at equilibrium for the same values of w and ϕ, as illustrated above. The first network configuration corresponds to a regular graph (where each agent has exactly three direct contacts), while the second network configuration is highly asymmetric, with one agent having two contacts, two agents having only one contact and one agent having no contact at all at equilibrium. This multiplicity of network equilibria, corresponding to different aggregate levels of crime, is consistent with the high unexplained variance in crime rates across locations usually documented in the literature.[29]

5 Concluding discussion

The empirical literature documents huge differences in crime rates across different social groups and/or locations displaying otherwise identical economic fundamentals. To account for this puzzle, the theoretical literature devises mechanisms of social influence whereby individual decisions feed each other and, altogether, generate a premium for the observed aggregate outcome (with respect to what would be observed if individual outcomes were merely juxtaposed to each other, without cross influences of any sort). Glaeser *et al.* (2002) and Horst and Scheinkman (2003) examine the incidence for empirical inferences and on the equilibrium of

[29]Glaeser *et al.* (1996) estimate that less than 30% of the variation in crimes rates across cities or subcity units can be explained by differences in observable local area characteristics.

and economy, respectively, of such *social multiplier* effects.[30]

The type of social interactions that generates social multiplier effects may take different forms. Indeed, the social setting can affect any of the determinants of individual behavior, namely, opportunities, expectations and preferences. Two important contributions analyze two possible incidences of social interactions on crime behavior.[31]

First, Sah (1991) examines the influence of the social surrounding on individual expectations. In the model, individuals' perceptions of punishment probabilities evolve endogenously with the information on the costs of crime these individuals gather locally, this information being in turn related to the level of local involvement in crime activities. The paper examines the coupled dynamics of the individual sense of impunity (or lack of), the associated individual crime behavior, and the local patterns of crime. It also related this joint dynamics to the dynamics of the aggregate crime rate.[32] Second, Glaeser *et al.* (1996) provide a model of crime decisions with positive interrelationships among such decisions. In the model, the positive covariance across agents' decisions about crime generates an overall variance in crime rates higher than predicted by the simple cost-benefit trade off at the individual level. The positive covariance is obtained with a population of ex ante heterogeneous agents composed of rational agents, who decide to become criminals after arbitrating the costs and benefits associated to this activity, and imitators, who simply blindly imitate the behavior of rational agents. Given a topology for social interactions (in the paper, agents are arranged on a circle), individual decisions taken by rational agents spill over nearby imitators and generate clusters of agents undertaking identical activities (either criminals or workers).[33] This model yields to an index of the degree of social interactions which is later estimated for a variety of different crimes in the U.S.

In our model, the pattern of interconnections among active criminals is modelled as a graph. Through their personal links with other criminals, and depending on the involvement in delinquent behavior of their network mates, agents acquire proper know-how on the crime business. Therefore, and contrarily to Sah (1991), social interactions do not affect the individual perception of the costs of crime but the true value of these costs suffered by active criminals. Here, the social setting is not conducive to a higher or a lower *sense of impunity*, but rather to a higher or a lower *real impunity* or vulnerability to punishment.

As in Glaeser *et al.* (1996), we show that criminal interconnections generate a premium on the aggregate crime level (with respect to the case with no social interactions), and that this social multiplier effect increases with the density of the pattern of connections. Our approach, though, departs from this paper in at least three respects.[34] First, rather than focusing on regular lattices, we model interaction structures as graphs,

[30]The empirical anomalies due to social multiplier type of effects can be traced back to the ecological versus individual correlation debate among sociologists during the 1950's (see, e.g., Robinson (1950)). Glaeser *et al.* (2002) is a breakthrough to this debate: the paper first constructs and estimator for the size of the social multiplier effect and then estimates this size in three areas: education, crime and group membership.

[31]Another related contribution is Verdier and Zenou (2004) where the focus is on the geographical space. If everybody believes that blacks are more criminal than whites (even if there is no basis for this), they show that ex ante identical agents who only differ by the color of their skin (blacks versus whites) may have very different outcomes in terms of crime behavior because of amplifying effects. It is because the authors consider the complete interactions of three markets (crime, labor and housing) and because workers rationally anticipate these interactions that they obtain these magnification results.

[32]See Goyal (2003) for a general overview of learning dynamics with local information gathering.

[33]Models where agents take a binary decision and local influences are embedded in a regular lattice topology belong to the general family of Ising models (or voter model). See, e.g., Fölmer (1974).

[34]Also, our model is not intended to provide an estimator for social interaction effects on crime decisions (and actually to estimate such social multiplier effect on crime).

and provide general results relating the geometry of the network links to individual and aggregate outcomes. Our framework thus allows for as many interaction structures as different graph geometries.[35,36]

Second, we work with an ex ante homogeneous population of agents. Agents have identical idiosyncratic features, and the only source of heterogeneity across agents stems from their network location and the topology of the local network surrounding each of them. This type of heterogeneity, not necessarily observable to the econometrician, influences both individual decisions and aggregate outcomes and, as shown in our analysis, may be responsible for the unexplained observed variance in crime rates.[37] Also, it is important to notice that, with general graphs, the influence that any two agents exert on each other varies with the pair of agents considered and their local network geometry. Here, the social multiplier effect aggregates local influences of different intensities scattered on the graph and tailored locally to the particular geometric features of the different parts of such graph. Besides obtaining a global social multiplier effect, our model can also account for the pattern and (potentially) uneven distribution of such social multiplier effects among subgroups of agents.[38]

Finally, we allow for the interaction structure to evolve endogenously on account of agents' actions, motivated by their own self-interest. It is important to notice that the multiplicity of equilibrium outcomes holds even when we allow for endogenous network formation, as shown in the example with $n = 4$ agents that we fully analyze. Our account of the unexplained variance in aggregate crime rates in terms of multiple equilibria, established in the first part of the paper, is thus robust to the endogenous formation of the interaction structure, an aspect that, so far, has been largely neglected in the literature.

[35] Graphs can display many both local (closely versus loosely-knitted) and global properties (high versus low average path length), and the range of graphs displaying different properties is wide.

[36] Note also the central role played in our analysis by the subgraphs induced on subsets of agents by the original graph, and the (potential) multiplicity of network architecture that such subgraphs may display.

[37] Indirect inference of these types of social interaction effects is nonetheless possible. For example, using spatial auto-regression techniques, Topa (2001) identifies significant correlations in unemployment across social contacts.

[38] The literature on social multiplier effects (or peer effects) is often silent about the precise mechanisms through which individuals influence each other, and seldom relate the shape and intensity of the influence agents exert on each other to the details of the underlying social interaction process. For a model of a process of information transmission among network related agents on a labor market context, see Calvó-Armengol and Jackson (2003a,b).

Appendix

Proof of Lemma 2: Taking first order conditions leads to the following best-response functions:

$$BR_i\left(e_{-i}\right)=\frac{1}{2}\left[1-\sum_{j\neq i}e_j-\phi\sum_{j\neq i}\left(1-g_{ij}\right)e_j\right],i\in N.$$

The equilibrium profiles e^* of $\Gamma^*\left(\phi,g\right)$ are the solutions to $BR_i\left(e^*_{-i}\right)=e^*_i$, $i\in N$. We obtain a linear system of n equations with n unknowns:

$$2e_i+\sum_{j\neq i}\left(1-\phi g_{ij}\right)e_j=1-\phi,i\in N \tag{3}$$

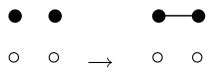
that we can write in matrix form $M\left(\phi,g\right)\cdot e=\left(1-\phi\right)\mathbf{1}_n$, where $m_{ii}=2$, $m_{ij}=1-\phi g_{ij}$ for all $i\neq j$ and $\mathbf{1}'_n=\left(1,\ldots,1\right)$. Denote by $\det\left(M\left(\phi,g\right)\right)$ the determinant of $M\left(\phi,g\right)$. We show that there exists some finite set $\mathcal{Z}\in\mathbb{R}$ such that $\det\left(M\left(\phi,g\right)\right)\neq 0$, for all $\phi\notin\mathcal{Z}$ and for all g on N.

Consider some network g. It is readily checked that $\det\left(M\left(\phi,g\right)\right)$ is a polynomial in ϕ of degree smaller than n.[39] Therefore, $\det\left(M\left(\phi,g\right)\right)$ has at most n different roots $\left\{\widetilde{\phi}_1\left(g\right),\ldots,\widetilde{\phi}_m\left(g\right)\right\}$, $m\leq n$, such that $\det\left(M\left(\widetilde{\phi}_i\left(g\right),g\right)\right)=0$ for all $1\leq i\leq m$. Given that there are exactly $2^{\frac{n(n-1)}{2}}$ different networks g on N, the set of values $\mathcal{Z}$ of ϕ such that $\det\left(M\left(\phi,g\right)\right)=0$ for some g on N is finite, with $\left|\mathcal{Z}\right|\leq n2^{\frac{n(n-1)}{2}}$. ∎

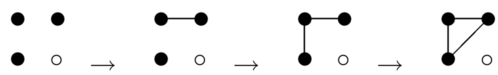
Example with $n=4$ agents located on a circle: Simple algebra shows that $e^*_1\left(g\left(1\right)\right)>e^*_1\left(g\left(1,2\right)\right)>e^*_1\left(g\left(1,3\right)\right)>e^*_1\left(g\left(1,2,3\right)\right)>e^*_1\left(g\right)$. Also, $e^*_2\left(g\left(1,2,3\right)\right)>e^*_1\left(g\left(1,3\right)\right)$ is equivalent to $2\phi^2+2\phi-1>0$. This polynomial of order two in ϕ has exactly one root $\widetilde{\phi}=\left(\sqrt{3}-1\right)/2$ contained in $\left(0,1\right)$, and the inequality holds if and only if $\phi>\widetilde{\phi}$. ∎

Endogenous networks with $n=4$ agents: We solve the game backwards. For each network configuration on $N=\{1,2,3,4\}$, we specialize and solve for the equilibrium equations (3). We analyze separately three cases with, respectively, two, three and four criminals. For each case, we establish the sequence of improving networks $g\rightarrow g'$, where g' improves upon g if either (a) two agents i and j in g such that $ij\notin g$ mutually gain by linking each other, and $g'=g\cup\{ij\}$, or (b) one player in g unilaterally gains by seceding some existing links $ij_1,\ldots ij_m\in g$, and $g'=g\backslash\{ij_1,\ldots,ij_m\}$.

Two criminals: For all $\phi\in\left(0,1\right)$, we have:

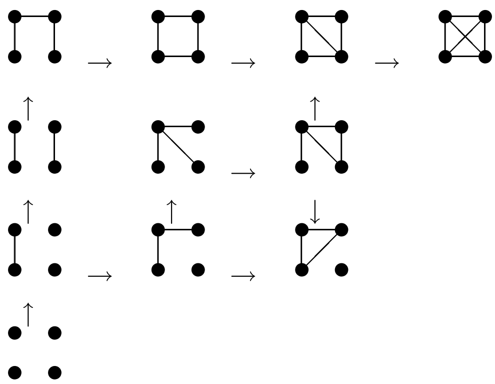


Three criminals: For all $\phi\in\left(0,1\right)$, we have:

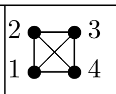
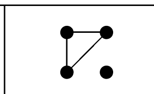
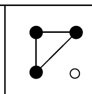
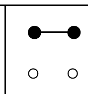
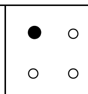
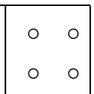


[39] Indeed, $\det\left(M\left(\phi,g\right)\right)$ is a polynomial of highest degree in ϕ when $g_{ij}=1$ for all $i\neq j$, in which case $\det\left(M\left(\phi,g\right)\right)=\left(1+\phi\right)^n+n\left(1-\phi\right)\left(1+\phi\right)^{n-1}$, which is a polynomial in ϕ of degree exactly n.

Four criminals: For all $\phi \in (0,1)$, we have:



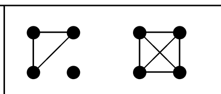
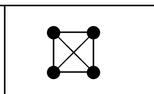
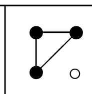
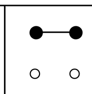
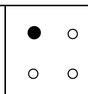
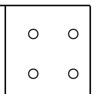
Given the previous sequences of improving paths, we can restrict to the following network configurations for the equilibrium analysis of the two-stage game, for which we compute the last-stage equilibrium effort levels $(e_1^*, \ldots, e_4^*)$:

						
e_1^*	$\frac{1-\phi}{5-3\phi}$	$\frac{1-\phi}{5-4\phi}$	$\frac{1-\phi}{4-2\phi}$	0	0	0
e_2^*	$\frac{1-\phi}{5-3\phi}$	$\frac{1-\phi}{5-4\phi}$	$\frac{1-\phi}{4-2\phi}$	$\frac{1-\phi}{3-\phi}$	$\frac{1-\phi}{2}$	0
e_3^*	$\frac{1-\phi}{5-3\phi}$	$\frac{1-\phi}{5-4\phi}$	$\frac{1-\phi}{4-2\phi}$	$\frac{1-\phi}{3-\phi}$	0	0
e_4^*	$\frac{1-\phi}{5-3\phi}$	$\frac{(1-\phi)(2-\phi)}{10-8\phi}$	0	0	0	0

Pairwise-comparisons of payoffs leads to the following inequalities:

$$\frac{1-\phi}{2} > \frac{1-\phi}{3-\phi} > \frac{1-\phi}{4-2\phi} > \frac{1-\phi}{5-4\phi} > \frac{1-\phi}{5-3\phi} > \frac{(1-\phi)(2-\phi)}{10-8\phi}, \text{ for all } \phi \in (0,1)$$

from which we deduce the pairwise-SPNE networks when $\overline{m} > \sqrt{w} \geq \underline{m}$, for the following upper and lower bounds on $\sqrt{w}$:

						
$\overline{m}$	$\frac{(1-\phi)(2-\phi)}{10-8\phi}$	$\frac{1-\phi}{5-3\phi}$	$\frac{1-\phi}{4-2\phi}$	$\frac{1-\phi}{3-\phi}$	$\frac{1-\phi}{2}$	$+\infty$
$\underline{m}$	0	$\frac{(1-\phi)(2-\phi)}{10-8\phi}$	$\frac{1-\phi}{5-3\phi}$	$\frac{1-\phi}{4-2\phi}$	$\frac{1-\phi}{3-\phi}$	$\frac{1-\phi}{2}$

∎

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