ANNALES D'ÉCONOMIE ET DE STATISTIQUE. – N° 71-72 – 2003

Does crime affect unemployment? The role of social networks*

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ABSTRACT. – In this paper, we consider a community of individuals that are embedded within a network of social relationships. Each individual has tight and permanent relationships with close friends and relatives (strong ties) as well as random and transitory interactions within the community (weak ties). Workers can either be employed or unemployed. Some workers do not even participate in the labor market because they are engaged in criminal activities. Unemployed workers can find a job through strong ties (assumed not to be criminals), weak ties (some of them being criminals) as well as through formal methods (such as advertisement or employment agencies). We show that crime rate within a community increases the unemployment rate of this community. Indeed, when the crime rate increases, weak ties become less valuable in terms of information content about jobs since the likelihood to interact with a criminal is higher. The overall job information available through personal contacts decreases, frictions in the labor market are exacerbated, and unemployment rises.This predicted interplay between crime and unemployment, grounded on the social setting, is reminiscent of the epidemic theory of ghettos.

La délinquance, source de chômage ? Le rôle des réseaux sociaux

RÉSUMÉ. – Dans cet article, les individus d'une communauté sont reliés entre eux par des liens sociaux. Ces liens sont de deux types: liens tenus et permanents avec des amis proches ou des parents (liens forts) et liens transitoires et aléatoires au sein de la communauté (liens faibles). Les individus peuvent soit prendre part au marché du travail, où ils sont employés ou chômeurs, soit devenir des délinquants. Les chômeurs recherchent un emploi à travers leur réseau de contacts constitués de liens forts (qui participent tous au marché du travail) et de liens faibles (dont certains sont délinquants), ainsi qu'à travers de procédures formelles telles que petites annonces, agences de recrutement, etc. Nous montrons que, au sein d'une communauté donnée, le taux de chômage augmente avec le taux de délinquance. En effet, une augmentation du taux de délinquance réduit la valeur des liens faibles pour la recherche d'un emploi en augmentant le nombre de délinquants rencontrés suivant cette modalité d'interaction. L'information utile à la recherche d'un emploi et accessible à travers les réseaux de contacts diminue, ce qui accentue les frictions du marché de l'emploi; le chômage augmente. La relation de cause à effet entre délinquance et chômage par le biais des interactions sociales établie dans cet article rappelle les mécanismes sous-jacents à la théorie épidémique des ghettos en sociologie.

* Part of this work was written while the first author was at Universidad Carlos III. We are grateful to Nuno Garoupa, Barbara Petrongolo and two anonymous referees for helpful comments and suggestions. Financial support from the Spanish Ministry of Science and Education through grants SEC2001-0973 and BEC2002-2130 and the Barcelona Economics Program – CREA is gratefully acknowledged. The usual disclaimer applies.

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1 Introduction

It is commonly observed for most countries that unemployment and crime rates are positively correlated. It is much more unclear whether this relationship means that unemployment causes crime, crime causes unemployment, or other factors cause both. In other words, the sign of the correlation is clear but the direction of the causality is not. One direction of the causality, unemployment affects crime, has received wide attention in the literature, but the reverse one has been largely neglected. The aim of this paper is to provide a simple theoretical framework that explains how crime rate affects unemployment rate through social networks.

Our approach is twofold. First, we recognize and take explicit account of the crucial role social networks play in a labor market context by matching job-seekers with vacancies. To this purpose, we construct an explicit micro scenario where the structure of personal contacts and the job information transmission process is spelled out in detail, and derive from this framework the aggregate rate at which job matches occur. This endogenous matching function depends on the unemployed worker and vacant firm pools and on the social network underlying players talks. In particular, increasing the size of the social network alleviates labor market frictions and reduces unemployment.

Second, we focus on the patterns of social interaction and distinguish two main types of social contacts. Individuals may either interact within their close set of friends and relatives (we refer to such permanent intragroup interactions as *strong ties*) or with any other member in the broad community they are embedded in (we label these random intergroup pairwise meetings as *weak ties*). As the community involvement in criminal activities increases, random encounters or weak ties interaction with community mates become both less valuable for job-seeking purposes (as the likelihood to interact with criminals out of the labor force increases) and less frequent (as the deterioration of the social surrounding drives individuals away from community life).

According to the previous results, when the prevailing crime rate increases, the community involvement to the labor market is reduced and generates a subsequent deterioration of the access to jobs through personal contacts (essentially weak ties). Labor market frictions are thus exacerbated and result in a higher unemployment rate. Our model thus offers a novel explanation for the reversed causation running from crime to unemployment that emphasizes the role of social networks.[1] Most of the empirical studies conducted so far have focused instead on the positive impact unemployment may have on

1. SAH [1991] and GLAESER *et al.* [1996] emphasize the role social networks may play in the decisions to commit crime and argue that this social embeddedness of individual decisions may account for the observed high variability of crime rates across space that remains even after controlling for social and economic background variables. AKERLOF and YELLEN [1994] focus on the fact that crime occurs in a social setting so that community norms and values have a key role in controlling crime. More precisely, they show that the rewards of criminal activity and the likelihood of punishment cannot be understood apart from the community (the social environment of criminals), its sense of justice, and its interaction with potential criminals. See also REISS and TONRY [1986] for the importance of communities in understanding crime.

crime levels, often neglecting to test for the potential two-way causality between the macrosociological variable (the area crime rate) and the macroeconomic one (the state unemployment rate). Some exceptions, though, handle explicitly this issue and conclude that both unemployment affects crime and, reciprocally, crime affects unemployment.[2] Crime is thus both a cause and an effect of unemployment. Partly generated by (voluntary or involuntary unemployment) at the state level it also feeds-back upon and contributes to sustaining high unemployment rates.

The paper is organized as follows. Section 2 presents the model of job matching emphasizing the role of social networks for job-seeking purposes. The model of social embeddedness that distinguishes between strong and weak ties is presented in Section 3, where the crime rate is explicitly incorporated in the pattern of social interactions. Section 4 presents our main result, where crime is presented as a possible causal factor for unemployment. Finally, Section 5 discusses the main literature on crime and unemployment, locates our contribution within this research area and concludes.

2 Personal contacts and job matching

It is widely known and documented that job seekers partly rely on personal contacts to gather information about jobs.[3] To simplify matters suppose that each worker (either employed of unemployed) are permanently socializing with s individuals who may transmit information about jobs. In other words, at each period, each worker is embedded within a social network of size s. Let u be the unemployment rate at some period. Assume that the s individuals constituting the network of social contacts for the time being are chosen at random at each period from a continuum of workers of mass n. Therefore, all workers have both the same number of direct acquaintances equal to s (symmetry) and the same number of employed and unemployed direct contacts equal respectively to $(1-u)\,s$ and us (uniform mix). Suppose that at the beginning of each period, workers hear about a job offer through formal methods with probability v, equal to the economy vacancy rate. At every period, matches between workers and firms depend upon the current network of social contacts of size s and the current state of the economy given by the unemployment rate u and the vacancy rate v. At the end of each period, currently employed workers lose their jobs with some probability δ. This process is taken to depend only on the general state of the economy and hence is treated as exogenous to the labor market.

2. We refer the reader to section 5 for a review of empirical evidence of this two-way causality between crime and unemployment.

3. Sociologists and labor economists have produced a broad empirical literature, initiated in the 1950s, describing and revealing the central role of networks of personal contacts for job-finding purposes. MONTGOMERY [1991] provides a complete account of this empirical work illustrating the pervasiveness of contact networks in labor markets and their relative effectiveness among sex, race and age groups. Although the use of contact networks varies with the social group considered, a rough estimate indicates that about half of all jobs are filled through contacts.

Unemployed workers find jobs through two different channels. They either find their job directly through *formal* methods – such as advertisement or employment agencies – with probability v, or they gather information about jobs through *informal* methods – in our case, the network of social contacts. Denote by $P(s,u,v)$ the individual probability of hearing a job from personal contacts through word-of-mouth communication. We now compute this probability, following CALVÓ-ARMENGOL [2004].[4]

Let $e = 1 - u$, the individual probability of any worker being employed. Consider first one particular direct personal contact of some unemployed worker. The unemployed worker may then be informed about a job vacancy from this personal contact with probability ve, equal to the probability that this personal contact is both employed (probability e) and informed about a job offer (probability v). But this currently employed and informed worker may instead transmit this information to any other unemployed worker belonging to his direct network. To account for such information sharing effect, we have to weight the probability ve by an appropriate parameter that we now compute. Consider one currently unemployed worker and assume that some direct contact of him is currently employed and aware of a redundant job slot to be transmitted within his network of close friends. With probability $e^{s-k-1}(1-e)^k$ there are exactly $k+1$ potential recipients of the job information possessed by the employed friend (that is, $k+1$ unemployed direct contacts of such employed and informed worker), including the unemployed worker we are focusing on. Assuming that all direct contacts are treated on an equal footing, the individual conditional probability to benefit from this job information held by a direct friend is $1/(k+1)$. The information sharing parameter can thus be computed as:[5]

$$\sum_{k=0}^{s-1} \binom{s-1}{k} \frac{e^{s-k-1}(1-e)^k}{k+1} = \frac{1-e^s}{s(1-e)}$$

We can thus deduce that some particular contact is fruitful to find a job with probability $ve\left(1-e^s\right)/s(1-e)$ and none of the s current network members are helpful with probability $\left[1 - ve\left(1-e^s\right)/s(1-e)\right]^s$. Therefore, the individual probability of finding a job through friends is given by:

$$P(s,u,v) = 1 - \left[1 - \frac{ve\left(1-e^s\right)}{s(1-e)}\right]^s \qquad (1)$$

At each period, currently unemployed workers locate their jobs (when they do) either through formal methods – probability v – or through informal

4. BOORMAN [1975] is the first paper that computes a closed-form expression for a probability similar to the one obtained here.

5. Note that $(1-e^s)/(1-e) = 1 + e + \cdots + e^{s-1}$ reflecting the fact that the negative information sharing constraint is not linear in the network size.

means – probability $(1-v)\,P\,(s,u,v)$. The matching function for our labor market where workers partly rely on personal contacts to find a job is thus given by:[6]

$$(2) \qquad m(s,u,v) = u\,[v + (1-v)\,P(s,u,v)]$$

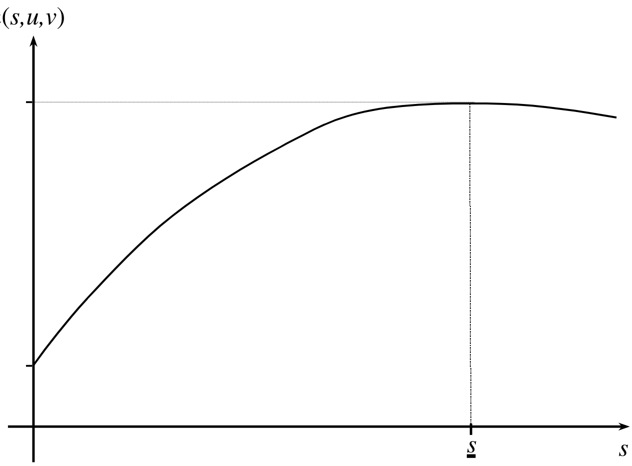
The previous close-form expression gives the aggregate rate at which job matches occur as a function of the unemployed worker and vacant firm pools, and the social network underlying players talks. This endogenous matching function is derived from an explicit micro scenario where the structure of personal contacts and the job information transmission process is spelled out in detail. Our framework can be seen as an extension of the standard urn-ball model, where firms play the role of urns, workers play the role of balls, and balls (workers)\ are randomly placed in urns (firms). Because of a coordination failure in this random placing, not all pairs are matched exactly. Rather, this uncoordinated process yields to overcrowding in some jobs and no applications to others. Such coordination failures are the sources of frictions captured by the matching function.[7] In our context, the network of personal contacts allows for a (partial) replacement of redundant jobs thus reducing coordination failures and alleviating matching frictions, whose intensity is now explicitly related to network size. The link between $m(s,u,v)$ and the network size s is precisely a key element of our model, that we now examine in detail.

Increasing the number of personal contacts broadens the potential employment channels, and more connections increase the potential job information available to any worker. But all workers being now better connected, the information they possess is also shared among a bigger group of individuals. One's direct contacts are indeed likely to be in contact with many other unemployed workers in the population, and the job information to which one may have acceded privately is now likely to reach someone else instead. In other words, direct contacts are beneficial whereas indirect connections are detrimental. As a result, network size s has a positive impact on the matching rate $m\,(s,u,v)$ by reducing labor market frictions, but this positive impact exhibits diminishing returns to network size (see Figure 1). In particular, in very dense networks (characterized by high values of s), the information sharing constraints may even outweigh the positive impact of more contacts, and increasing the network size may then slow down information transmission through contacts and reduce the matching effectiveness. Denote by $\overline{s}$ the threshold value above which m decreases with s.[8]

From now on we restrict to the generic case where network size has a positive impact on the matching rate by reducing labor market frictions. Graphically, the relationship between the unemployment rate u and the

6. To be more precise this matching function corresponds to the rate at which job matches occur per unit of time. It suffices therefore to multiply $m(s,u,v)$ by the population size to get the number of matches per unit of time.
7. See PETRONGOLO and PISSARIDES [2001], section 3.2 for an exhaustive and critical survey of existing microfoundations of the matching function related to the urn-ball model.
8. We refer the reader to CALVÓ-ARMENGOL [2004] for more details, including a proof of the strict concavity of $m\,(\cdot,u,v)$ and the fact that this function asymptotically decreases.

FIGURE 1
The matching function $m(s,u,v)$ ***versus network size*** s



vacancy rate v determined by the matching function $m\,(s,u,v)$ can be represented by a downward sloping curve in the unemployment-vacancy space called the Beveridge curve. The Beveridge curve is deduced from the steady-state condition on flows equating flows in with flows out of unemployment.[9] An increase in s reduces market frictions and thus shifts the Beveridge curve downwards as, holding the arrival rate v fixed, unemployment decreases with s. To determine the steady-state labor market equilibrium characterized by equilibrium unemployment and vacancy rates $\left(u^*,v^*\right)$ we still have to determine the labor demand curve. Indeed, the labor market equilibrium $\left(u^*,v^*\right)$ satisfies both a free-entry condition for firms and a steady-state condition on unemployment flows, and is obtained at the intersection of the respectively associated labor demand curve and Beveridge curve.

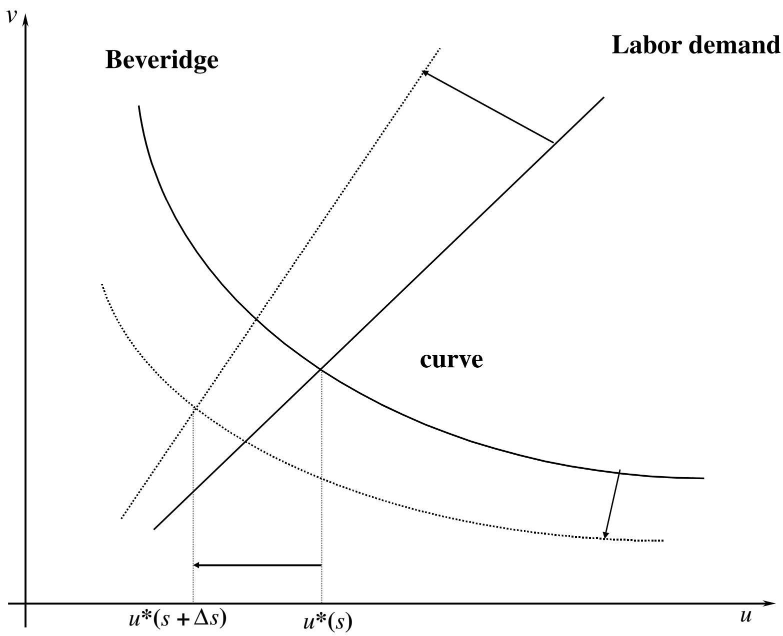
Following PISSARIDES [2000], we assume that firms post vacancies up to a point where the steady-state profit of a vacancy is zero, which implies that the value of a job at steady state is equal to the expected search cost. The corresponding equation can be represented by an upward sloping curve in the unemployment-vacancy space called the labor demand curve.[10] Increasing the

9. Formally, the steady-state flow equation is $m(s,u,v) = \delta(1-u)$.

10. More formally, suppose that firms and workers are all identical. A firm is a unit of production that can either be filled by a worker whose production is y units of output or be unfilled and thus unproductive. We denote by γ the search cost for the firm per unit of time, by w the wage paid by the firms when a match is realized and by r the discount rate. We assume that the wage is exogenous (our focus is not on wage determination but on the impact of the network of personal contacts on labor market outcomes). At period t, the intertemporal profit of a filled job and of a vacancy are denoted respectively by $I_{F,t}$ and $I_{V,t}$. Denote by r the discount rate. With discrete time: $I_{F,t} = y - w + \frac{1}{1+r}\left[(1-\delta)I_{F,t+1} + \delta\, I_{V,t+1}\right]$ and $I_{V,t} = -\gamma + \frac{1}{1+r}\left[(1-m/v)I_{V,t+1} + (m/v)\; I_{F,t+1}\right]$ where m/v is the job filling rate. In the steady state, $I_{F,t} = I_{F,t+1} = I_F$ and $I_{V,t} = I_{V,t+1} = I_V = 0$ (free entry condition) from which we deduce that $(y-w)\,m(s,u,v)/v = \gamma\,(r+\delta)$. In other words, the value of a job is equal to the expected search cost. See CALVÓ-ARMENGOL and ZENOU [2001] for more details.

network size s reduces search costs (and therefore increases vacancy posting) by alleviating market frictions and thus shifts the labor demand curve upwards as, holding the unemployment rate u fixed, the vacancy rate now increases (see Figure 2).

FIGURE 2
***Equilibrium unemployment** u^* **versus network size** s*



When the size of the social network increases, workers gather more and more information about jobs from a broader set of available personal contacts through word-of-mouth communication. The labor market frictions are thus alleviated and the equilibrium unemployment rate u^* decreases. Reciprocally, when the network size decreases, the diffusion of job information is slowed down and exacerbates labor market frictions. Accordingly, the (steady-state) unemployment rate u^* increases. To summarize,

PROPOSITION 1: *Assume that* $s < \overline{s}$. *At steady state,* $\partial u^* / \partial s < 0$.

3 A model of social embeddedness

So far, we have focused on the relationship between the size s of the network of personal contacts and the equilibrium unemployment rate u^*. We now examine the inner composition of the social network and distinguish between those personal contacts that participate to the labor force (and who may provide access to information about jobs) and those personal contacts that have dropped out from the labor market and are instead engaged in criminal activities (and who cannot vehiculate any information about jobs).

The previous analysis takes explicit account of the crucial role social networks play in matching job-seekers with vacancies and concludes at the positive impact social connectedness and the pervasiveness of personal connections have on employment rates. Implicit to these arguments is the assumption that all unemployed workers embedded within the social network of size s considered are actively searching for a job, meaning that none of them is out of the labor force. In other words, any worker (employed or unemployed) belonging to the social network participates in the labor market and is eager to collect, diffuse or benefit from any available (source of) information about job opportunities. Of course, within a socially connected community, some individuals may work or search for a job while others may not participate in the labor market and engage instead in criminal activities. We investigate the relationship between the value of a social setting for job-seeking purposes and the prevailing crime rate within a given community. We first need to introduce a taxonomy of social contacts that we classify either as *strong ties* or as *weak ties*.

Consider a large society or community with n individuals. In this society, individuals belong to mutually exclusive groups that, for simplicity, are assumed to be of equal size. Such groups consist on knit clusters of f close friends or relatives, and the intragroup social interactions take the form of tight and permanent relationships that we denote *strong ties*. If all social relations were of the strong tie type, the community would be fragmented into n/f different clusters with no communication whatsoever among them. We assume on the contrary that individuals belonging to different groups may randomly meet each other. Such random and transitory intergroup interactions are referred to as *weak ties*. Weak ties are crucial for the diffusion of job information as they provide bridges between close-knits of individuals and allow job seekers to access information in distant parts of the social structure through personal contacts. Empirical evidence suggests in fact that weak ties relay useful job information more frequently than strong ties.[11] As GRANOVETTER [1995] points out: « weak ties [are] strong in connecting people to information beyond what they typically [have] access to through their strong ties, since [their] acquaintances are less likely than [their] close friends to know one another, and are more likely to move in circles different from and beyond [their] own » (p. 148).

Assuming that social contacts occur through pairwise meetings, at any point in time a given individual may either interact with his close set of friends (permanent or strong ties) or with some other individual in the society (transitory or weak ties). Following MONTGOMERY [1994], let ω represent the proportion of social interaction that occurs outside the close set of friends or relatives and within the broad community ($0 \leqslant \omega \leqslant 1$). Therefore, $1 - \omega$ is the proportion of strong tie interactions, and the average number of contacts is

11. The predominance of weak ties in connecting workers to jobs is for instance documented in GRANOVETTER [1995]. Among those workers in his sample that found their job through contacts, 83.4% that report information was collected from a weak tie with whom they interact only « occasionally » or even « rarely ». See also GRANOVETTER [1983].

given by $(1-\omega) f + \omega n$. Given that not all contacts need to participate in the labor force (some may be involved in criminal activities), the size s of the social group relevant for job seeking purposes is generally lower than this number, that is, $s \leqslant (1-\omega) f + \omega n$. We now compute the value of s.

As seen in the foregoing, individuals looking for jobs rely partly on personal contacts. Unemployed workers can locate jobs through strong ties (permanent intragroup relationships), weak ties (random intergroup meetings), as well as through formal methods (such as advertisement or employment agencies). Since only workers participating in the labor market (*i.e.* either currently employed or searching actively for jobs) are useful to gather information about job opportunities, not all personal contacts are valuable. Since permanent relationships are both a matter of personal choice (close friends) and inherited social structure (relatives), *we assume that any of the f strong ties of a job seeker participate in the labor force*. However, weak ties are a matter of random encounters, and thus can include individuals who are not looking for a job and perform illegal activities such as crime. We denote by ρ the fraction of community individuals that commit crime (who are thus not participating in the labor market)[12] and, therefore, *only a fraction* $1-\rho$ *of weak ties is considered by a job seeker as reliable sources of job information*. Implicitly, we are thus assuming that criminals who drop out of the labor force do not have any information about job opportunities. We can decompose the total average number of contacts available to some individual as follows:

$$\underbrace{(1-\omega) f + \omega n}_{\text{total number contacts}} = \underbrace{(1-\omega) f + \omega (1-\rho) n}_{\text{contacts in the labor force}} + \underbrace{\omega \rho n}_{\text{criminals}}$$

Therefore, for any worker in the labor force (either currently employed or unemployed), the average number s of personal contacts constituting a valuable potential source of information at any point in time is given by:

$$s = (1-\omega) f + \omega (1-\rho) n \tag{3}$$

It is easy to see that s increases with the number of contacts, would it be strong ties ($\partial s/\partial f > 0$) or weak ties ($\partial s/\partial n > 0$). Beyond this network size effect, the composition of personal contacts also affects s. In particular, a higher proportion ω of weak ties increases the (valuable) network size s, that is, $\partial s/\partial \omega > 0$ whenever $(1-\rho) n > f$, that is, the total number of non criminal weak ties $(1-\rho) n$ is higher than the size f of a close-knit.

Although we do not provide here an explicit model of network formation,[13] it seems quite natural to assume that ω is negatively correlated with ρ, that is, $\omega'(\rho) < 0$, since a job seeker embedded in a community with a higher proportion of criminals is more likely to give more weight to interactions with

12. Of course, we could have considered a model in which workers commit crime while employed. This would have complicated the analysis without altering our main results.

13. There is a recent and growing literature on the formation of networks that now provides a ready set of tools for analyzing this problem. See DUTTA and JACKSON [2002] for an overview.

strong ties in order to (at least partially) withdraw himself from an adverse social environment.[14] Formally,

$$s = [1 - \omega(\rho)]\, f + \omega(\rho)(1 - \rho)\, n \tag{4}$$

where

$$\frac{\partial s}{\partial \rho} = \omega'(\rho)\,[(1 - \rho)\, n - f] - \omega(\rho)\, n$$

Assuming that $\omega'(\rho) < 0$, one can check that $\partial s/\partial \omega > 0$ implies that $\partial s/\partial \rho < 0$. In words, the average number s of personal contacts that constitute a valuable source of job information increases with the community quality whenever a relative increase in weak ties interaction is also beneficial. Recall that a necessary and sufficient condition for $\partial s/\partial \omega > 0$ to hold is $(1 - \rho)\, n > f$.

Suppose on the contrary that the number of non criminal weak ties is lower than non criminal strong ties that is, $(1 - \rho)\, n \leqslant f$. This situation corresponds to a highly deteriorated social setting. The sign of the partial derivative $\partial s/\partial \rho$ now strongly hinges on the elasticity η of the proportion ω of weak ties with respect to the proportion ρ of criminals in the community. With our assumption on $\omega(\rho)$, this elasticity is negative since an improvement of the social surrounding (*i.e.* a decrease in ρ) exacerbates community-type interaction (*i.e.* increases ω). In other words, a more intense community involvement in illegal activities triggers a relative increase in strong tie interaction within close-knits whose members are devoted to legitimate activities. One can check that $|\eta| < n\rho/f$ implies that $\partial s/\partial \rho < 0$. In words, whenever individuals respond less than proportionally to a deterioration of their social surrounding by withdrawing themselves from the outside community (or, equivalently, if a reduction of criminals belonging to the job-seeker community generates an investment in weak ties interaction of lower magnitude), the average number of personal contacts that are valuable for job-seeking purposes increases with the community quality.

Assuming that any of these two conditions hold, we have $\partial s/\partial \rho < 0$. This negative impact of the rate of criminals on the valuable network size can be decomposed as follows. First, as the crime rate increases, random encounters (weak ties) with community friends become less valuable for job-seeking purposes since the likelihood to interact with a criminal is higher. Second, since individuals tend to react to such an increase by isolating themselves from the outside world and spending more time with their close set of friends and relatives (strong ties), the frequency of weak ties diminishes. Therefore, as the community involvement to the labor market decreases, the access to jobs transmitted through personal contacts is deteriorated. Formally,

PROPOSITION 2: *If either* $(1 - \rho)\, n > f$ *or both* $(1 - \rho)\, n \leqslant f$ *and* $|\eta| < n\rho/f$*, then* $\partial s/\partial \rho < 0$.

14. Empirical evidence suggesting that exposure to crime indeed shapes the community pattern of social interactions can be found in ALBA *et al.* [1994].

4 Crime affects unemployment

In fact, varying the crime rate in some community affects both the proportion of interactions that occur through weak ties and their information content for job-seeking purposes. Indeed, when ρ increases, the valuable part of the social network is reduced, thus leading to higher labor market frictions that generate a subsequent increase in the equilibrium unemployment rate. Formally,

$$\frac{\partial u^*}{\partial \rho} = \underset{(-)}{\frac{\partial u^*}{\partial s}} \times \underset{(-)}{\frac{\partial s}{\partial \rho}} > 0$$

When the crime rate increases, weak ties become less valuable in terms of information transmission about jobs since the likelihood to interact with a criminal is higher. The quality of information transmitted by strong ties is not affected since there are no criminals among them. This implies that the overall job information through personal contacts has decreased and the quality of the social network has deteriorated. As a result, frictions in the labor market increase, finding a job through word-of-mouth communication is more difficult and, therefore, unemployment rises. We can summarize the previous results with the following proposition.

PROPOSITION 3: *Suppose that $s < \overline{s}$. If either $(1-\rho)\,n > f$ or both $(1-\rho)\,n \leqslant f$ and $|\eta| < n\rho/f$, then, at steady state, $\partial u^*/\partial \rho > 0$.*

One should observe that in areas where the crime rate is high, the unemployment rate should also be quite high. This typically corresponds to urban ghettos where high crime and unemployment rates are the norm rather than the exception. Therefore, to reduce unemployment in these areas, the local government should either ameliorate the information about jobs (so that workers rely less on their social networks) or reduce the crime rate.

As a result and contrary to the literature on crime (see our discussion in section 5) where the focus is on the impact on local unemployment rate (or on the duration of unemployment of a particular individual) on the behavior of this individual, in the present paper, we tackle two different issues. First, we focus on the reverse relation, *i.e.* the impact of crime rate on unemployment. Second, we do not model the individual decision to engage in criminal activities (this is taken to be exogenous) but we provide an explanation on the positive link between a macro sociological variable – the community crime rate – and a macro economic variable – the community unemployment rate – through the micro sociological determinants of job search, that is social networks.

5 Discussion

5.1 Empirical evidence

The usual empirical studies focus on the role of unemployment as a determinant for crime. Yet, the empirical time-series and cross-sectional studies conducted so far fail to reach consensus for most crimes.[15] However, most results indicate that unemployment has an unambiguous positive impact on property crimes, a particular type of criminal activities. For example, CHIRICOS [1987] finds in his review very strong evidence that unemployment is positively correlated with property crimes, though results are stronger for studies in the 1970s than in earlier periods. In his most recent survey, FREEMAN [1999] shows that most time series analyses conclude that crime rates rise with joblessness. For example, examining 10-year changes in crime and economic conditions across 582 countries from 1979 to 1989, GOULD *et al.* [2001] estimate that a one-point increase in unemployment raised property crimes by 2.2 percent. LEE [1993] gives comparable results for 58 Standard Metropolitan Statistical Areas for a similar time-period, from 1976 to 1989. Finally, RAPHAEL and WINTER-EBMER [2001] show that nearly 40 percent of the decline in property crime rates during the 1990s is attributable to the concurrent decline in the unemployment rate. Furthermore, all studies agree that persons prone to unemployment are more likely to commit crimes and that people who commit crimes are more likely to do so during spells of unemployment (see in particular FARRINGTON *et al.* [1986], SAMPSON and LAUB [1993], and WITTE and TAUCHEN [1994]).

The (potential) simultaneity between crime and unemployment, largely neglected by most studies, has been explicitly addressed in at least three empirical papers with controversial results. Indeed, CORMAN *et al.* [1987] conclude at no GRANGER causality in both directions, whereas THORNBERRY and CHRISTENSON [1984] and BUSHWAY and ENGBERG [1994] provide separate evidence for both directions of the causality (namely, unemployment affects crime but also and, reciprocally, crime affects unemployment).

The conclusion we can draw from these empirical studies is the following. Assuming one-way causality and making no adjustments for this simultaneity effect should lead to estimates of the effect of unemployment on crime systematically biased upwards.[16]

5.2 Epidemics of crime and unemployment

It is commonly argued that unemployment causes crime, that is, $\rho = \rho(u)$ with $\partial\rho/\partial u > 0$. The theoretical motivation behind this direction of causality is straightforward. Involuntary unemployment decreases potential earnings

15. FREEMAN [1999] provides a thorough survey of the empirical literature on crime and the labor market.

16. RAPHAEL and WINTER-EBMER [2001] do not explicitly test for two-way causality but discuss it informally and rule out reverse causation by instrumenting state unemployment rates.

and income from licit activities thereby lowering the opportunity cost to commit crime. Consequently, rational offenders tend to participate more in the criminal sector as illegal activities now offer higher (relative) returns. The relationship between the individual decision of committing crime and the unemployment rate should thus be unambiguously positive.[17]

Crime may also cause unemployment, that is, $u = u(\rho)$, with $\partial u / \partial \rho > 0$. The general theoretical approach to crime as a possible determinant of unemployment is twofold. First, crime may affect the supply-side of the labor market, at the individual level, either by reducing the reemployment probability of formerly convicted offenders, stigmatized by their past criminal behavior or identified as low-productivity workers (see *e.g.* Dickens *et al.*, [1989] and RASMUSSEN [1996]), or by diverting criminals from participation in licit activities such as legitimate employment, perceived as less profitable than current illegal behavior. Second, crime may affect the demand-side of the labor market, at the local level, by driving away existing firms, pushing away potential new-settlers and thereby slowing employment growth down.

Our model offers a novel explanation for the reversed causation running from crime to unemployment that emphasizes the role of social networks. We do not predict anything about the individual behavior, *i.e.* the fact that criminals tend to be more unemployed than non-criminals. Rather, we predict that when the crime rate is quite high in a (local) area, the unemployment rate of this (local) area is more likely to be high. As stated above, a (macro) sociological variable – the community crime rate – affects a (macro) economic variable – the state unemployment rate – through the (micro) sociological determinants of job search that we fully recognize and explicitly model. We show that an increase in the community involvement in criminal behavior deteriorates the network of personal contacts, reduces the accessibility of unemployed workers to existing job opportunities, exacerbates labor market frictions and, therefore, increases unemployment.

This two-way causality between crime and unemployment implies that models aiming at joint crime and unemployment determination are likely to have multiple equilibria. Crime participation rates and unemployment rates might thus differ among two societal groups even when they face similar economic fundamentals. Moreover, areas experiencing high crime rates tend to experience, simultaneously, high unemployment rates.[18] This remark is

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17. The seminal contribution on the economics of crime is BECKER [1968]. For a survey on this literature, see GAROUPA [1997]. For a recent theoretical model of criminal activity and the labor market see BURDETT *et al.* [1999]. A very stylized model predicting a positive effect of unemployment on crime could be the following. Suppose that the individual expected returns to being involved in criminal activities are $\beta V - (1-\beta) P - z$, where V is the booty, $1-\beta$ is the probability to be caught, P the corresponding penalty, and z an idiosyncratic reluctance to commit crime, uniformly distributed on $[0, \overline{z}]$. Denote by b the unemployment benefit. Then, an unemployed individual being offered to participate in a criminal activity accepts it whenever $\beta V - (1-\beta) P - z > b$, that is, with probability $\pi = \beta V - (1-\beta) P - b$ (assuming that $\overline{z}$ is high enough, that is, $\overline{z} > \beta V - (1-\beta) P - b$, and that $\beta V - (1-\beta) P > b$). Suppose that unemployed workers hear of some available criminal activity they could participate in with some exogenous probability α, that employed workers never have access to this type of information, and that criminals remain so unless they are in jail. Then, the crime rate evolves as follows: $c_{t+1} = \beta c_t + \alpha \pi u_t$, implying that current unemployment feeds crime. At the steady state, $c = \frac{\alpha}{1-\alpha} \pi u$.
18. An indirect evidence of the positive interplay between crime and unemployment can be found in WESTERN and BECKETT [1999]. See also WACQUANT [1999].

consistent with the observed unequal geographical pattern of crime and unemployment. It is also consistent with models that view ghettos as communities that have experienced epidemics of social problems.[19] Unemployment and crime feed on each other and escalate together, like an epidemic process. This epidemic linkage between crime and unemployment implies that slight initial variations in unemployment and/or crime rates, or in the patterns of social interaction relating these two aggregate variables, can have drastic implications for long run observed outcomes. In other words, the collective history of the societal group determines which equilibrium is eventually reached.[20]

Given these positive externalities between the aggregate crime and unemployment, both problems should be treated together. Indeed, the epidemics also operate the other way round, and any improvement in one direction (say, reduction of the crime rate) leads to a subsequent reduction in the other direction (reduction of the unemployment rate), which feeds back again to the first direction, and so on. Also, given that our predicted synergy between labor and crime outcomes is identified at the community level, the policy programs should tackle both plagues at once and target one particular community, rather than spreading resources away. ▼

19. CRANE [1991]'s epidemic theory of ghettos claims that social problems (here, unemployment and crime) are contagious and spread though the social background within which individuals are embedded. In particular, this theory stresses the fact that models with multiple equilibria exhibit critical mass properties, namely, the prevalence of a problem tends to gravitate toward some relatively low-level equilibrium while incidence of this problem stays below a critical point, whereas below such critical point, the process escalates and a high-level equilibrium is eventually reached.

20. CALVÓ-ARMENGOL and JACKSON [2004] analyze the patterns and dynamics of employment and wages in a model where agents obtain information about job opportunities through an explicitly modeled network of social contacts. They find similar contagion effects in drop-outs rates within close-knits which may account for the observed inequality in wages and employment between blacks and whites in the US economy.

• References

AKERLOF G., YELLEN J.L. (1994). – « Gang behavior, law enforcement, and community values », H.J. Aaron, T.E. Mann and T. Taylor (eds.), in *Values and Public Policy*, Washington: The Brooking Institution, ch.7, p. 173-209.

ALBA R.D., LOGAN J.R., BELLAIR P.E. (1994). – « Living with crime: the implications of racial/ethnic differences in suburban location », *Social Forces*, 73, p. 395-434.

BECKER G. (1968). – « Crime and punishment: an economic approach », *Journal of Political Economy*, 76, p. 169-217.

BOORMAN S.A. (1975). – « A Combinatorial Optimization Model for Transmission of Job Information Through Contact Networks », *Bell Journal of Economics*, 6, p. 216-249.

BURDETT K., LAGOS R., Wright R. (1999). – « Crime, inequality, and unemployment », unpublished manuscript, University of Pennsylvania.

BUSHWAY S., ENGBERG J. (1994). – « Panel data VAR analysis of the relationship between crime and unemployment », unpublished manuscript, Carnegie Mellon University.

CALVÓ-ARMENGOL A. (2004). – « Job contact networks », *Journal of Economic Theory* 115, p. 191-206.

CALVÓ-ARMENGOL A., ZENOU Y. (2001). – « Job-matching, social network and word-of-mouth communication », CEPR Working Paper 2797.

CALVÓ -ARMENGOL A., JACKSON M.O. (2004). – « The Effects of Social Networks on Employment and Inequality », *American Economic Review*.

CHIRICOS T. (1987). – « Rates of crime and unemployment: An analysis of aggregate research evidence », *Social Problems*, 34, p. 187-211.

CORMAN H., JOYCE T., LOVITCH N. (1987). – « Crime, deterrence and the business cycle in New York city: A VAR approach », *Review of Economics and Statistics*, 69, p. 695-700.

CRANE J. (1991). – « The epidemic theory of ghettos and neighborhood effects on dropping out and teenage childbearing », *American Journal of Sociology*, 96, p. 1226-1259.

DICKENS W., KATZ L., LANG K., SUMMERS L. (1989). – « Employee crime and the monitoring puzzle », *Journal of Labor Economics*, 7, p. 331-347.

DUTTA B., JACKSON M.O. (2002). – « On the Formation of Networks and Groups », Introductory chapter forthcoming in *Models of the Formation of Networks and Groups*, edited by B. Dutta and M.O. Jackson, Springer-Verlag: Heidelberg. http://www.hss.caltech.edu/∼jacksonm/Jackson.html

FARRINGTON D.P., GALLAGHER B., MORLEY L., ST. LEDGER R.J., WEST D.J. (1986). – « Unemployment, school leaving and crime », *British Journal of Criminology*, 26, p. 335-356.

FREEMAN R.B. (1999). – « The economics of crime », in *Handbook of Labor Economics*, O.Ashenfelter and D. Card (eds.), Amsterdam: North Holland, p. 3529-3571.

GAROUPA N. (1997). – « The theory of optimal law enforcement », *Journal of Economic Surveys*, 11, p. 267-295.

GLAESER E., SACERDOTE B., SCHEINKMAN J. (1996). – « Crime and social interactions », *Quarterly Journal of Economics*, 111, p. 507-548.

GOULD E., WEINBERG B., MUSTARD D. (2001). – « Crime and local labor market opportunities in the United States: 1979-1997 », *Review of Economics and Statistics*, forthcoming.

GRANOVETTER M. (1983). – « The strength of weak ties: A network theory revisited », *Sociological Theory*, 1, p. 201-233.

GRANOVETTER M. (1985). – « Economic action and social structure: The problem of embeddedness », *American Journal of Sociology*, 91, p. 481-510.

GRANOVETTER M. (1974)(1995). – *Getting a Job: A Study of Contacts and Careers*, 2nd edition, Canbridge (MA): Harvard University Press.

LEE D. (1993). – « An empirical investigation of the economic incentives for criminal behavior », Unpublished manuscript, Harvard University.

MONTGOMERY J. (1991). – « Social networks and labour market outcomes: Toward an economic analysis », *American Economic Review*, 81, p. 1408-1418.

MONTGOMERY J.D. (1994). – « Weak ties, employment, and inequality: An equilibrium analysis », *American Journal of Sociology*, 99, p. 1212-1236.

PETRONGOLO B., PISSARIDES C. (2001). – « Looking into the black-box: A survey of the matching function », *Journal of Economic Literature*, forthcoming.

PISSARIDES C.A. (2000). – *Equilibrium Unemployment Theory*, 2nd edition, Cambridge (MA): MIT/Press.

RAPHAEL S., WINTER-EBMER R. (2001). – « Identifying the effect of unemployment on crime », *Journal of Law and Economics*, forthcoming.

RASMUSSEN E. (1996). – « Stigma and self-fulfilling expectations of criminality », *Journal of Law and Economics*, 39, p. 519-543.

REISS A.J., TONRY M. (1986). – *Communities and Crime, Crime and Justice: A Review of Research*, Chicago: University of Chicago Press.

SAH R.K. (1991). – « Social osmosis and the patterns of crime », *Journal of Political Economy*, 99, p. 1272-1295.

SAMPSON R.J., LAUB J.H. (1993). – *Crime in the Making: Pathways and Turning Points Through Life*, Cambridge (MA): Harvard University Press.

THORNBERRY T.P., CHRISTENSON R.L. (1984). – « Unemployment and criminal involvement: An investigation of reciprocal causal structures », *American Sociological Review*, 49, p. 398-411.

WACQUANT L. (1999). – *Les Prisons de la Misère*, Paris: Edition Raisons d'Agir.

WESTERN B., BECKETT K. (1999). – « How unregulated is the US labor market? The penal system as a labor market institution », *American Journal of Sociology*, 104, p. 1135-1172.

WILSON W.J. (1987). – *The Truly Disadvantaged: the Inner City, the Underclass, and Public Policy*, Chicago: University of Chicago Press.

WITTE A.D., TAUCHEN H. (1994). – « Work and crime: An exploration using panel data », *Public Finance*, 49, p. 155-167.