Abstract

Social networks help workers to find jobs more easily. But those jobs need not be in occupations in which workers can fully exploit their abilities. If so, then social contacts can generate mismatch between a worker’s occupational comparative advantage and his actual productivity. As a result, economies that rely extensively on social networks can exhibit low labor force quality and low returns to firms’ investment, which in turn causes a depressed level of aggregate productivity. In this sense, social networks can be inefficient and may prevent an economy from fully exploiting its potential. We employ US and European data to test the implication that social networks reduce productivity by inducing mismatch. We find that jobs obtained through contacts do indeed lead to lower wages, and we show that this wage discount, of the order of 6%-7%, is driven by self-selection of people with a larger endowment of contacts.

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1 Introduction

Friends and relatives are often recognized as a useful source of information for finding a job. And much research has emphasized the positive role of social contacts in helping people to find jobs.\footnote{See the empirical results in Holzer (1988) and the model in Mortensen and Vishwanath (1994), respectively.} For instance, in a number of studies for the US surveyed by Montgomery (1991), the share of workers reporting to have found their jobs through friends or relatives ranges from 24% to 74%, depending on the occupation and the locality of reference.

However, social contacts are usually acquired and maintained for other purposes and they typically help a worker to find a job only in specific occupations or segments of the labor market. Thus the availability of social contacts may lead a worker to decide to work in an occupation where his abilities are not fully exploited just because jobs in that occupation are found more easily.

In this paper we analyze the aggregate implications of the mismatch between workers’ comparative advantage and their occupational choices induced by social networks, in the context of a search model. We assume that workers are born in different locations—a specific city or a certain quarter of a given city, say—and that each location is specialized in a different occupation. Workers may have a comparative advantage in any occupation but they have more contacts in the location where they are born. Thus they face a trade-off between searching for a job in their native location, where they can exploit their connections to find a job, and searching for a job in the occupation where their comparative advantage is the greatest (and so is their wage) if they find a job. In equilibrium, the higher the worker’s endowment of social contacts, the greater is the comparative advantage needed to convince him to sever his social ties when searching for a job.

It may seem that social contacts are so cheap that everyone will use them. But the empirical evidence says otherwise. For instance, in the data base that we use in this paper, which covers three large US cities—Atlanta, Boston, and Los Angeles—in the early 1990s, a full 53% of respondents stated that they did not talk to relatives as a method of job search and 26% did not talk to friends.

In our model economy, mismatch is always too large relative to the social optimum, since workers do not internalize that, when their occupational choice follows their comparative advantage, they are actually improving the average quality of the labor force for that occupation. But when the average quality of the labor force improves, firms have greater incentive to create vacancies for that occupation and to operate with technologies which are more intensive in capital (provided that physical capital is complementary with workers’ ability). In this sense, the occupational choice triggered by comparative advantage generates a positive externality on the workers in
the market by simultaneously increasing the probability of finding a job and the stock of capital with which they work. Interestingly, the adverse effects of social networks on mismatch can be so strong that aggregate net income can even fall in response to an increase in the endowment of social contacts.

In one extension to the theoretical model we also endogeneize the endowment of social contacts in the economy by assuming that the value of social contacts is directly related to the employment rate, as suggested by recent empirical evidence (see Topa (2000)). When this happens, equilibria with a high employment rate and high mismatch can co-exist with one equilibrium where the employment rate is lower but mismatch is less of a concern. Indeed when the employment rate is high, social contacts are more informative in finding jobs. Thus workers decide to become employed in the occupation specific of their native location. But then the employment rate remains high, which indeed allows this equilibrium to be sustained, obviously at the cost of a large degree of mismatch and a depressed level of aggregate productivity. We refer to this situation as an underemployment trap.

One key prediction of the paper is that social networks may prevent the economy from fully exploiting its potential, due to the induced mismatch between workers’ occupational comparative advantage and their actual occupational choice. We test this hypothesis with data from the ”Multi-City Study of Urban Inequality, 1992-1994”, a survey carried out by the Inter-University Consortium for Political and Social Research (see Bobo et al. (2000)). This is a very useful data base for testing our model, since in it around one-half of workers declare to have found their last or current job through social contacts. Using these data, we first show that, there is indeed a significant wage discount for jobs found through networks, of the order of 7%. We are also able to show using both an instrumental variable that this wage discount is driven by self-selection: workers with a greater endowment of contacts choose to use them more to find a job even if they may have a comparative advantage in some other occupations. Both findings support the our theoretical model’s predictions.

In addition, data for 14 European countries from the European Community Household Panel (ECHP) over 1994-1998 confirm a wage discount for jobs found through networks of around 6%, and provide evidence that there is a tradeoff between quicker jobfinding and lower wages. These data also allow us to show, for European regions, that there is probably an aggregate negative productivity effect of social contacts, through mismatch.

We are not the first to analyze the effects of finding a job through contacts on wages. The literature has mostly focused on employee referrals, with mixed results. Granovetter (1974) examined a sample of 282 male professional and technical workers living in Newton (Mass.) in the early 1970s who had changed job in the past five years, and reported that those who found jobs through a personal contact had higher incomes than those who used more formal channels, more so for those whose contacts were occupational rather than social or familial. Corcoran, Datcher, and Duncan (1980)
analyzed separately the wages of four groups of workers, black men and women, and white men and women, aged 18 to 64, in the 1977 Panel Study of Income Dynamics. They did not find significant effects of having heard about the job from friends and relatives for white men and women, a premium for black men and a discount for black women. Whether the worker knew or received help from an employee of the firm did not have a significant effect, except for black women, for which the discount roughly disappeared. More recently, Simon and Warner (1992) present a model in which firms have imperfect information on job applicants’ characteristics and reduce the uncertainty about this signal by eliciting a subjective opinion from applicants’ acquaintances working for the firm. They study a 1972 sample of Natural and Social Scientists and Engineers, reporting that those who found jobs through employees already working at the firm or ”insiders” had a higher wage, while those who did through ”outsiders” had a wage discount. Lastly, Kugler (2002) presents a model in which gains from paying wages above market clearing are highest for firms hiring through employee referrals because of the peer monitoring role played by referees. She combines data from the 1982 National Longitudinal Survey of Youth, Krueger and Summer’s (1988) estimated wage premia from the 1984 Current Population Survey, and industry characteristics from the National Organizations Survey, finding that industries with a higher percentage of referred workers paid higher wage premia.

Contrary to this literature, our paper does not focus on referrals from current employees but, more broadly, on jobs found through social contacts. And, in particular, we analyze empirically the wages of young workers (up to 34 years old) with limited work experience, and on jobs found through friends and relatives rather than through professional contacts. Moreover, in our empirical analysis we are able to control for whether the person who helped finding the job worked at the same firm and show that our empirical results are robust to this control.

Closer to the spirit of our paper, within a standard search model with two types of workers, Santamaría-Garcia (2002) models social contacts as a cheap method of finding a job match, which is only available to connected agents. Empirically, Pistaferri (1999) found that Italian workers who find their jobs through informal job networks have significantly lower wages than those who do not, of the order of 4% once individual characteristics are taken into account.

Our paper relates to several other strands of the literature which have recently become very active. First, we contribute to the literature that has analyzed how social capital affects the functioning of the aggregate economy. Social contacts help the spreading of information and thus are a form of social capital in the sense of Coleman (1988). Our analysis points towards the importance of going deeper into the

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2See for example Knack and Keefer (1997) and Guiso et al. (2000).
3Indeed he states that “An important form of social capital is the potential for information that inheres in social relations (...). In this case relationships are valuable for the information they
sources and determinants of social capital, since not all of them necessarily promote an efficient functioning of the economy. Our analysis also gives one complementary explanation for why segregation by skill and occupation may persist so much from one generation to the other, as discussed by Borjas (1995). The literature has generally emphasized the role of peer effects as a mechanism of transmission of human capital from one generation to the next—a channel that can explain why a given spatial distribution of skills and occupations may persist across generations. Here we emphasize instead that inter-generational occupational and spatial mobility can remain low not because of intrinsic differences in workers’ human capital but because individuals choose to use their local connections to find jobs more easily.

We also contribute to some recent strands of the growth literature, which have emphasized how “social infrastructure” affects capital-labor ratios and aggregate productivity, as for example Hall and Jones (1999). We identify social networks as a possible reason why the average quality of the labor force and the return to firms’ investments may remain low.

The rest of the paper is organized as follows. Section 2 describes the model. Section 3 analyzes the equilibrium. Section 4 discusses the effects of social networks on firms’ investment. Section 5 contains the results on efficiency. Section 6 deals with the extension about the underemployment trap. Section 7 characterizes our empirical strategy. Section 8 describes the data and our empirical results and Section 9 concludes.

2 The model

We consider a static labor market populated by two unit masses of risk neutral workers and an endogenously determined mass of firms. Workers have an equal probability of being born in one of the two existing locations \( i = 1, 2 \). A location is intended to represent a city or a certain quarter of a given city.

2.1 Search frictions

Each location is specialized in a different economic activity, which results from differences in either sectorial production or job types. Either way, a job created in a given location is associated with a specific occupation. Each firm can create a job vacancy for a specific occupation at a cost \( c > 0 \). Each vacancy becomes a job when occupied by a worker.

Each location is characterized by a local labor market which is subject to search frictions. The underlying assumption is that vacancies for a specific occupation are heterogeneous and workers are suitable just for a specific subset of the available
vacancies for that occupation. Following Pissarides (2000), we model the total number of matches in location \( i \) by using a matching function \( m(V_i, U_i) \) where \( V_i \) and \( U_i \) denote, respectively, the number of vacancies for type-\( i \) occupation and the number of workers searching for that specific occupation, the latter measured in efficiency units of search. The matching function is assumed to be homogeneous of degree one, increasing, concave, and continuously differentiable.

Accordingly, a vacancy for occupation \( i \) finds a suitable worker with probability

\[
q(\theta_i) = \frac{m(V_i, U_i)}{V_i} = m(1, \frac{1}{\theta_i}),
\]

which is decreasing in the level of labor market tightness, \( \theta_i = V_i/U_i \), in the given location. Searching for a job is a full time activity. Accordingly, the worker must choose the occupation where he would like to work before starting to search for a job.

The worker’s social background (i.e. the type of friends acquired during childhood or the parents’ connections) affects the kind of social contacts used by the worker when searching for a job. Contacts are local in the sense that they can be better exploited if a worker searches for a job in the location where he is born. A worker can also rely on other formal channels to find a job for which he is suitable (reading newspapers ads, or contacting private or public employment agencies, say). Formally, workers differ in their endowment of efficiency units of search. A worker that searches for a job in the same location where he is born is endowed with \( \phi + \eta \) efficiency units of search. Conversely, if he searches in a different location he is endowed with only \( \phi \) units. The parameter \( \eta \) reflects social network intensity, while \( \phi \) is directly related to the efficiency of formal recruitment channels.\(^4\)

Summing up, a worker born in location \( j \) who searches for a job in location \( i \) finds a suitable job with probability

\[
(\phi + \eta - \eta|j - i|) p(\theta_i)
\]

where

\[
p(\theta_i) = \frac{m(V_i, U_i)}{U_i} = \theta_i q(\theta_i).
\]

Finally we assume that \( m(V_i, U_i) \leq \min(V_i, U_i/(\phi + \eta)) \) to ensure that probabilities are properly defined and that

\[
\lim_{x \to 0} q(x) = 1 \quad \text{and} \quad \lim_{x \to \infty} q(x) = 0,
\]

in order to guarantee that, in each labor market, the equilibrium value of \( \theta \) is interior.

\(^4\)Within a standard search model with two types of workers, Santamaria-Garcia (2002) models social contacts as a cheap method of finding a job match, which is only available to connected agents.
2.2 Comparative advantage

Workers are heterogenous in their productivity level and can have a comparative advantage in either occupation. Specifically, any worker can produce at least $y > c$ units of output in a given occupation. But a worker employed in the occupation where he has a comparative advantage is able to produce $y(1 + m\tilde{\mu})$, where $\tilde{\mu}$ is a random drawing from a uniform distribution with support on $[0,1]$ which measures the extent of worker’s comparative advantage. The parameter $m$ reflects the importance of the associated specialization gains.

With probability $f$, a worker has a comparative advantage in the occupation specific of the location where he is born. Otherwise, with probability $1 - f$, the worker needs to move to exploit his comparative advantage. The value of $f$ tends to be close to one when social connections also enhance workers’ productivity in the job. Conversely, $f$ tends to be close to zero when a worker can attain a productivity edge by exploiting his cultural identity in an environment dominated by a different culture. In this sense the value of $f$ is inversely related to the benefits of cultural diversity.

2.3 Wage determination

After a match is formed, the outside options of both the firm (leaving the vacancy unfilled) and the worker (remaining unemployed) are worth zero. Thus there is a surplus from the hiring which is equal to the worker’s output. We assume that wages are determined according to the Generalized Nash Bargaining Solution where the worker’s and the firm’s bargaining powers are $\beta$ and $1 - \beta$, respectively. Thus the worker’s wage is equal to a fraction $\beta$ of his output in the firm.

3 Equilibrium

In equilibrium the level of labor market tightness is the same in both locations ($\theta_1 = \theta_2$). Hence the equilibrium is characterized by the common level of labor market tightness $\theta$ and a threshold $\mu^*$ which identifies the level of comparative advantage beyond which a worker severs his social ties to fully exploit his comparative advantage.

3.1 Occupational choice

Consider a worker who is born in location $i$ but has a comparative advantage in occupation $j \neq i$. Such a worker decides to take advantage of his comparative advantage, $\tilde{\mu}$, only if it is so large that it pays him off to sever his social ties when searching for
a job. This is the case if $\tilde{\mu}$ is such that
\[
p(\theta_i)(\phi + \eta)\beta y < p(\theta_j)\phi \beta y(1 + m\tilde{\mu}).
\]
But, since in equilibrium $\theta_1$ and $\theta_2$ are equal, there exists a critical reservation threshold
\[
\mu_* = \min(1, \frac{\eta}{m\phi})
\]  
(OC)
such that a worker chooses to sever his social ties in order to exploit his comparative advantage only if this is greater than $\mu_*$. The parameter $\mu_*$ gauges the degree of mismatch in the labor market. Mismatch is at its maximum when $\eta$ is greater than $m\phi$, so that $\mu_*$ is equal to one. In this case, social ties entirely determine any occupational choice.

3.2 Free entry

Since wages are equal to a fraction $\beta$ of the worker’s output, the expected income from opening a vacancy in a given location is equal to
\[
V = q(\theta)(1 - \beta) E(\tilde{y})
\]  (2)
where $E(\tilde{y})$ denotes the expected output of a hired worker. To compute $E(\tilde{y})$ notice that the number of workers, measured in efficiency units of search, in each labor market is equal to:
\[
U = (\phi + \eta)f + \phi(1 - f)(1 - \mu_*) + (\phi + \eta)(1 - f)\mu_* = \phi + \eta f + \eta(1 - f)\mu_*,
\]  (3)
which is the sum of the search efficiency units of each of the three types of workers that participates in the labor market. First, there is a measure $f$ of workers who search for a job in their native market and have a comparative advantage in the occupation specific of that location. Secondly, there is a measure $(1 - f)(1 - \mu_*)$ of workers who search for a job in a market different from the one where they are born so as to exploit their comparative advantage. Finally, there is a measure $(1 - f)\mu_*$ of workers who decides to search for a job in their native market even if exploiting their comparative advantage would require them to search in the other market.

Thus the expected output of a hired worker is equal to
\[
E(\tilde{y}) = \frac{(\phi + \eta)f}{U} \int_0^1 y(1+m\tilde{\mu})d\tilde{\mu} + \frac{\phi(1-f)(1-\mu_*)}{U} \int_{\mu_*}^1 y(1+m\tilde{\mu})d\tilde{\mu} + \frac{(\phi + \eta)(1-f)\mu_*}{U} y,
\]
which says that $E(\tilde{y})$ is a weighted average of the expected output of each of the three types of workers with weights equal to the firm’s probability of contacting the given type. Notice that the larger the endowment of efficiency units of search of a
given worker type the larger is the firm’s probability of matching with them. After rearranging it follows that

\[ E(\tilde{y}) = yM(\mu_s) \]  

(4)

where

\[ M(\mu_s) = 1 + \frac{m \phi + \eta f - \phi(1 - f)(\mu_s)^2}{\phi + \eta f + \eta(1 - f)\mu_s}. \]

which is decreasing in \( \mu_s \) since an increase in the degree of mismatch in the labor market reduces the average productivity of matches. When either \( \mu_s = 0 \) or \( f = 1 \), workers’ occupational choices are entirely determined by comparative advantage and their productivity is at its maximum, so that \( M(\mu_s) = 1 + m/2 \). Conversely, when both \( \mu_s = 1 \) and \( f = 0 \), social ties entirely determine workers’ occupational choice even if all workers should move to exploit their comparative advantage. In this case the average worker’s productivity is at its minimum, \( M(\mu_s) = 1 \).

Creation of vacancies till the exhaustion of all rents implies that \( V = c \) which, after substituting (4) into (2), leads to the following free-entry condition:

\[ \frac{c}{g(\theta)} = (1 - \beta)yM(\mu_s), \]  

(FC)

which, given (1), has a unique interior solution for any given \( \mu_s \) if \((1 - \beta)y \geq c\), an inequality that we hereafter assume. Condition (5) identifies a negatively sloped relationship between \( \mu_s \) and \( \theta \). As the degree of mismatch in the labor market increases, the average worker’s productivity falls, thus firms create less vacancies and labor market tightness falls till the point where the free entry condition is restored.

The equilibrium of the model can be analyzed in the \( \mu_s - \theta \) space and it is identified by the unique point where the free-entry condition (FE) and the optimal occupational choice condition (OC) cross.

### 3.3 Comparative statics

Notice that the expected productivity of a job conditional on being filled through social contacts is equal to

\[ E(\tilde{y} | \text{network}) = \frac{\eta f}{\eta f + \eta(1 - f)\mu_s} y \left( 1 + \frac{m}{2} \right) + \frac{\eta(1 - f)\mu_s}{\eta f + \eta(1 - f)\mu_s} y \]

\[ = y \left[ 1 + \frac{m}{2} \frac{\eta f}{\eta f + \eta(1 - f)\mu_s} \right], \]

that is equal to the weighted average of the expected productivity of a worker who searches for a job in his native market and has a comparative advantage in the occupation specific of that location, which has value \( y(1 + m/2) \), and the expected
productivity of a worker who chooses not to sever his social ties in spite of having a comparative advantage elsewhere, whose value is \( y \).

By an analogous reasoning, one can obtain that the expected productivity of a job conditional on being filled through formal channels,

\[
E(\tilde{y} \mid \text{formal}) = y \left\{ 1 + \frac{m}{2} \left[ 1 - (1 - f) (\mu^*)^2 \right] \right\}
\]

which can easily proved to be greater than \( E(\tilde{y} \mid \text{network}) \). Since the worker’s wage is equal to a fraction \( \beta \) of his output in the firm, the following is immediate:

**Proposition 1** Jobs found through social contacts pay on average a lower wage than jobs found through formal channels.

To analyze the effects of an increase in social network intensity notice that, given (OC), as \( \eta \) increases, \( \mu^* \) also increases. Consequently, \( M(\mu^*) \) falls both because the increase in \( \eta \) makes relatively more likely a match with a worker using his contacts—that on average is relatively unproductive—, \( \partial M/\partial \eta < 0 \) (see the Appendix), and because the increase in the degree of mismatch induced by the increase in \( \eta \) implies that the quality of the labor force worsens, \( \partial M/\partial \mu^* < 0 \). But as the expected profitability of a match falls, firms’ incentive to create new vacancies is reduced and, given (FE), labor market tightness falls. Thus:

**Proposition 2** As social network intensity increases, the degree of mismatch also increases, so that the average worker’s productivity and labor market tightness both fall. As a result, in equilibrium, the probability of finding a job by using formal channels, \( \phi p(\theta) \), decreases, while the effect on the worker’s probability of finding a job by using social contacts, \( (\phi + \eta)p(\theta) \), is generally ambiguous.

## 4 Capital Investment

We next extend the model to introduce firm’s investment in physical capital.

### 4.1 Firm’s capital

Upon entering the market, the firm has to choose which technology the worker operates in case of hiring. Opting for a specific technology involves the choice of a given level of capital \( k \). Upon meeting the worker, and before hiring him, the firm has to decide whether to install the required equipment and pay the installation costs \( rk \) where \( r \) is the unit cost of capital.

Specifically, we assume that firm’s investment affects workers’ productivity so that

\[
y = Ak^\alpha, \quad (5)
\]
where \( \alpha \) is greater than zero and strictly less than \( 2/(2 + m) \) which guarantees that, at the firm’s profit-maximizing level of capital, all matches yield a positive surplus. Since each worker obtain as a wage a fraction \( \beta \) of the surplus he generates in case of hiring (equal to worker’s output minus the cost of installing capital), the value of a vacancy is given by

\[
V = \max_k q(\theta) (1 - \beta) [Ak^\alpha M(\mu_*) - rk] \tag{6}
\]

where the term in square brackets evaluates the expected surplus from hiring a worker. By considering the first order condition in (6), it follows that the firm’s optimal level of capital is equal to

\[
k_* = \left[ \frac{A\alpha M(\mu_*)}{r} \right]^{\frac{1}{1-\alpha}}, \tag{7}
\]

which substituted in (5) allows us to compute first

\[
y = A^{\frac{1}{1-\alpha}} \left[ \frac{\alpha M(\mu_*)}{r} \right]^{\frac{\alpha}{1-\alpha}}, \tag{8}
\]

and then the expected surplus from hiring a worker, so as to obtain

\[
yM(\mu_*) - rk_* = [M(\mu_*)]^{\frac{1}{1-\alpha}} H \tag{9}
\]

where

\[
H = (1 - \alpha) \left( \frac{\alpha}{r} \right)^{\frac{\alpha}{1-\alpha}} A^{\frac{1}{1-\alpha}},
\]

which we assume to be greater than \( c \) to ensure an interior solution. But after substituting this expression into (6), imposing the free entry condition, \( V = c \), we get

\[
\frac{c}{q(\theta)} = (1 - \beta) [M(\mu_*)]^{\frac{1}{1-\alpha}} H, \tag{FE’}
\]

which is analogous to (5).

Furthermore, a worker born in location \( i \) whose comparative advantage is in occupation \( j \neq i \), decides to sever his social ties only if his comparative advantage \( \tilde{\mu} \) is such that

\[
p(\theta_i)(\phi + \eta)\beta (y - r\tilde{\mu}) \leq p(\theta_j)\phi\beta [y(1 + m\tilde{\mu}) - rk_*].
\]

But then from (9) it follows that, in equilibrium, the critical reservation threshold that governs worker’s occupational choice \( \mu_* \) solves an equation analogous to (2) which reads as

\[
\mu_* = \min \left( 1, \frac{\eta}{m\phi} [1 - \alpha M(\mu_*)] \right). \tag{OC’}
\]

As we show in the appendix, (OC’) always has a unique solution in \( \mu_* \) which is increasing in the \( \eta/m\phi \) ratio. Given (7), (8) and (FE’) it the we obtain the following
Proposition 3 An increase in the level of social network intensity reduces not only labor market tightness but also firms’ investment. Consequently, the productivity of each worker falls.

Interestingly, one can see that the greater is the elasticity of output with respect to capital, $\alpha$, the greater is the impact of a given increase of $\eta$ on $\mu_*$. Given (FE’), this also implies that the impact of a given increase of $\eta$ on labor market tightness is also larger. These results imply that when firms’ investment is endogenous, the adverse effects of social contacts on average labor productivity and labor market tightness are magnified.

5 Welfare

In this section we analyze the welfare properties of our economy. First, we analyze the main features of the first best allocation. Then we analyze the welfare properties of the equilibrium allocation. We then show that social contacts may lead to a reduction in social welfare.

5.1 The first best allocation

Since workers and firms are risk neutral, social welfare, $W(\theta, \mu_*)$, is equal to the sum of aggregate output net of the vacancy creation costs produced in each location. Notice that it is a function of the level of labor market tightness and the degree of mismatch in the labor market. Formally,

$$W(\theta, \mu_*) = 2[\phi + \eta f + \eta(1 - f)\mu_*] \left[ p(\theta) y M(\mu_*) - \theta c \right]$$

where the first term in square brackets measures the number of search efficiency units in each of the two locations while the second term represents the output, net of vacancy creation costs, that each search efficiency unit generates.

Maximization with respect to $\theta$ and $\mu_*$ in (10) allows us to characterize the first best allocation. Specifically, by deriving with respect to $\theta$, it follows that the socially optimal level of labor market tightness, $\theta_s$, solves

$$[1 - \gamma(\theta_s)] q(\theta_s) y M(\mu_*) = c$$

(11)

where $\gamma(\theta)$ is the elasticity of the matching function with respect to $U$ and can be computed as $\gamma(\theta) = \frac{q(\theta) + \theta q'(\theta)}{q(\theta)}$. Analogously by deriving with respect to $\mu_*$, using (11) and after taking into account that $\mu_*$ can not exceed 1, it follows that the socially optimal level of mismatch is such that

$$\mu_* = \min \left( 1, \frac{q(\theta_s)}{\phi m} \left[ 1 - [1 - \gamma(\theta_s)] M(\mu_*) \right] \right),$$

(12)
which immediately implies the following

**Proposition 4** The degree of mismatch in the competitive economy is always greater than in the first-best allocation.

Differently from each worker in the economy, the social planner realizes that mismatch reduces the average productivity of labor and consequently the profitability of creating new vacancies. By internalizing this effect the social planner always opts for a lower degree of mismatch.

### 5.2 The equilibrium allocation

We next evaluate the welfare properties of the equilibrium allocation of the competitive economy. To do so we evaluate the marginal social value of an increase in the level of labor market tightness and mismatch at the allocation that arises in equilibrium. Specifically, deriving with respect to \( \theta \) and then using (FE) and after some rearranging we get

\[
\left. \frac{\partial W}{\partial \theta} \right|_{\text{EQ}} = \frac{2c[\beta - \gamma(\theta)]U}{1 - \beta},
\]

so that the level of labor market tightness is generally inefficient. This inefficiency is of the type first pointed out by Hosios (1990): it is due to the conjunction of search frictions and bargaining in the labor market. The anticipated division of the surplus, that results from bargaining between firms and workers, plays a crucial role in encouraging or discouraging firms to create new vacancies. Opposite to Walrasian prices, the bargaining powers \( \beta \) and \( 1 - \beta \) do not adjust to reflect the marginal social value of a vacancy. When, for instance, workers are “too strong” (\( \beta > \gamma(\theta) \)), firms appropriate too little surplus and so they create too few vacancies.

Interestingly, by deriving with respect to \( \mu^*_s \) in (10), using (FE) and after some rearranging it follows that

\[
\left. \frac{\partial W}{\partial \mu^*_s} \right|_{\text{EQ}} = -2\theta c(1 - f)\eta,
\]

which is negative. Thus at the competitive allocation the degree of mismatch is always too large. Intuitively, this arises because workers do not internalize the adverse effect that an increase in mismatch has on vacancy creation (and on firm’s investment had capital been endogenous). Then the next proposition immediately follows:

**Proposition 5** The first best level of social welfare can be attained through a dual policy that comprises a subsidy to mobility and either a subsidy (when workers are too strong) or a tax (when workers are too weak) to vacancy creation.
5.3 Inefficient social contacts

An increase in the level of social contacts raises mismatch, so that the average productivity of a job falls. Such effect can be so large that, as a result of the increase in $\eta$, aggregate net income can even fall. In this sense social contacts can be inefficient. This outcome is the result of the inefficiently high degree of mismatch in the competitive economy. Indeed we show in the Appendix the following

**Proposition 6** At the first best allocation an increase in social network intensity always raises the level of aggregate net income.

Social contacts works as a grease that allows the diffusion of information and are a source of social capital that may help the smooth functioning of the labor market, if used properly.

In the competitive economy, however, social contacts also raise the degree of mismatch in the labor market. Specifically using (FE) to substitute for $\theta$ in (10) it follows that the level of social welfare of the competitive equilibrium can be written as

$$W(\theta, \mu_*)|_{eq} = \frac{2Uc\beta\theta}{1-\beta}. \tag{13}$$

But then, taking logs, deriving with respect to $\theta$ in (13) and after using (FE) and (OC) to calculate the ultimate effect of an increase of $\eta$ on $\theta$ and $\mu_*$, respectively, it follows that

$$\frac{d\ln W}{d\eta}|_{eq} = \frac{d\ln U}{d\eta} + \frac{1}{\gamma(\theta)} \frac{d\ln M}{d\eta}. \tag{14}$$

The first term is positive and it captures the grease effect of social networks. The second is negative and it is the result of the inefficiently high level of mismatch in the labor market. It then immediately follows that social networks may lead to a reduction in social welfare and may therefore be inefficient.$^5$ For example, $\frac{d\ln W}{d\eta}|_{eq}$ is surely negative when the grease effect of social contacts is mild while the deadweight loss of the fall in vacancy creation induced by the increase in mismatch is large –a case which (as shown in the Appendix) necessarily arises when $\gamma(\theta)$ is close to zero. In brief we have proved the following

**Proposition 7** An increase in the level of social contacts may lead to a reduction in aggregate net income.

---

$^5$One can show that this is more likely to be the case once firms’ investment is endogenous. When so, mismatch affects not only vacancy creation but also firms’ investment and the adverse effects of an increase in mismatch on output are magnified.
In the Appendix we show that an increase in social contacts always leads to an increase in net output when the adverse effects of a given degree of mismatch on productivity are low, which is the case when either $f$ is close to one or $\eta$ (and therefore $\mu_*$) is close to zero. But when $\eta$ tends to increase, the degree of mismatch in the labor market also tends to increase, and further increases in the level of social contact may lead to a reduction in welfare. Interestingly, if we let $\bar{\gamma}$ denote the elasticity of the matching function with respect to labor when $\eta = \phi m$ (so that $\mu_* = 1$), then we show in the Appendix that $\left. \frac{d \ln W}{d \eta} \right|_{\text{eq}}$ is negative for this value of $\eta$ if $(1 - \bar{\gamma})(2 - f) > 1$. This implies that there does exist a welfare maximizing level of social contacts, beyond which social contacts reduce social welfare and are necessarily inefficient.

6 Underemployment traps

So far we have assumed that the social network intensity is unrelated to structural features of the economy. This is clearly a simplifying assumption. For example Topa (2000) documents that the most valuable social contacts to find a job are those with employed people. Thus, generally social network intensity is positively related to the employment rate of the given location.

To capture this relation, we could assume that each worker has $F \leq 1$ friends and that the worker’s social contacts which are valuable to find a job correspond to the fraction $e$ of those friends who are employed, so that

$$\eta = Fe.$$  \hfill (15)

In general equilibrium $e$ coincides with the employment rate which is equal to

$$e = \frac{p(\theta)}{2} [\phi + \eta f + \eta (1 - f) \mu_*].$$  \hfill (16)

As in Benabou (1993), this way of reasoning is intended to reflect the situation that would arise in an equilibrium of an overlapping generation model where, during childhood, workers acquire their social contacts with the employed workers of that time and then enter the labor market when adult.

Underemployment is usually perceived as a situation where the employment rate is high, but workers do not fully exploit their abilities. We next show that when (15) holds, an underemployment trap can emerge where employment is high, so social contacts are very useful to find a job thereby inducing workers to search for a job in their native market even if they may have a comparative advantage in some other occupation.

Indeed, after using (16) to substitute for $e$ in (15) and then solving for $\eta$ it follows that

$$\eta = \frac{F \phi p(\theta)}{1 - F [f + (1 - f) \mu_*] p(\theta)}$$  \hfill (17)
which substituted into (OC) yields the following expression for the critical level of worker’s comparative advantage beyond which a worker chooses to sever his social ties:

\[ \mu^* = \min \left( 1, \frac{Fp(\theta)}{m - mF[f + (1 - f)\mu^*]p(\theta)} \right). \]  

(OC”)

Notice that the right hand side of (OC”) is increasing in \( \theta \), thus at \( \mu^* \) equal to one, (OC”) is a vertical line in the \( \mu^* - \theta \) space, see Figure 1. Conversely, when \( \mu^* \) is less than one (OC”) can be expressed as

\[ p(\theta) = \frac{\mu^*}{\frac{\epsilon}{m} + F\mu^*[f + (1 - f)\mu^*]}. \]

which is a concave function of \( \mu^* \) reaching a maximum at \( \mu^{**} = [m(1 - f)]^{-1/2} \). Interestingly, \( \mu^{**} \) is less than one (and OC” is not monotonically increasing) only if the specialization gains are sufficiently large.

Since the free entry condition (FE) remains unchanged it immediately follows that the equilibrium is represented by the point where the negatively sloped relation implied by FE crosses the (OC”) relation. Thus Figure 1 immediately implies that if \( \mu^{**} \) is less than 1, multiple equilibria tend to arise in the model (in the figure A, C and D are equilibria of the labor market). Multiple equilibria would also arise if \( \eta \) was
assumed to be inversely related to the degree of labor mobility which would imply a positive relation between $\eta$ and $\mu_\ast$. Summing up, we have shown the following

**Proposition 8** When the level of social network intensity is positively related to either the employment rate or the degree of workers’ mobility, an equilibrium with low mismatch can coexist with one where mismatch is high. Multiple equilibria are more likely when the specialization gains are large.

Given Proposition (6), the different equilibria can not be generally ranked in terms of welfare since they just differ in terms of social contacts intensity.

### 7 Empirical strategy

The model has several empirical implications, both micro and macroeconomic. We focus on three of them, spelled out below.

#### 7.1 Proposition 1

Proposition 1 states that jobs found through social contacts pay on average a lower wage than jobs found through formal channels. This implication can be tested in several ways. We follow an instrumental variable (IV) approach.

Our wage determination model could be briefly described as:

$$w_i = \begin{cases} w_{1i} = \alpha + u_{1i}, & \text{if contact used } (d_i = 1) \\ w_{2i} = \beta + u_{1i} + u_{2i}, & \text{if no contact used } (d_i = 0) \end{cases}$$

(18a)

where the worker chooses $d_i = 1$ whenever the gain from using contacts (in terms of reduction of the expected unemployment spell), $g_i$, exceeds the wage differential $w_{2i} - w_{1i}$. So we have $d_i = 1$ if and only if

$$g_i > \beta - \alpha + u_{2i}$$

(19)

and $d_i = 0$ otherwise. We may think that the gain from using contacts $g_i$ is partly explained by the worker’s endowment of contacts $e_i$ so that

$$g_i = \gamma e_i + v_i.$$

Assume that the variable $e_i$ is independent of $u_{1i}$, $u_{2i}$ and $v_i$. And, for simplicity, assume also that $u_{1i}$, $u_{2i}$ and $v_i$ have zero mean.

The observed wage of the worker can be written written as

$$w_i = \alpha d_i + \beta (1 - d_i) + [u_{1i} + u_{2i}(1 - d_i)].$$

(20)
The OLS regression

\[ w_i = a_0 d_i + a_1 (1 - d_i) + \text{error} \]

will then yield

\[ a_0 = \alpha \]

and

\[ a_1 = \beta + E(u_{2i}|d_i = 0) > \beta, \]

which imply that the OLS estimate of the wage premium of a job found through contacts will be

\[ a_0 - a_1 = \alpha - \beta - E(u_{2i}|d_i = 0) < \alpha - \beta. \]

In words, the OLS regression will tend to underestimate \( \alpha - \beta \) due to self-selection. Workers with a high \( u_{2i} \) tend to choose \( d_i = 0 \) and so, even if \( \alpha = \beta \), it may appear that jobs accessible through contacts pay lower wages (have lower productivity) on average than jobs not accessible through contacts.

The problem with estimating \( \alpha - \beta \) in the OLS regression is that the variable \( 1 - d_i \) is correlated with the error term. The classical way of solving this problem consists of finding an instrumental variable that explains a worker’s decision to use contacts, \( d_i \), but is uncorrelated with the worker’s productivity, \( u_{1i} \) and \( u_{2i} \). Under our assumptions, a proxy for \( e_i \) would do it.

In a two-stage version, the IV estimator will first produce an estimate

\[ \hat{d}_i = E(d_i|e_i) \]

and then find the OLS estimate of the regression

\[ w_i = b_0 \hat{d}_i + b_1 (1 - \hat{d}_i) + \text{error}. \]

Since, by construction, \( \hat{d}_i \) is orthogonal to \( u_{1i} \) and \( u_{2i} \), the estimates of \( b_0 \) and \( b_1 \) should provide consistent estimates of \( \alpha \) and \( \beta \).

### 7.2 Other tests

We also check two other elements of the model. First, an assumption of our model is that social contacts help find jobs more quickly. This creates, for some workers, a tradeoff from using contacts: they can find a job more quickly, but one which does not fully exploit their comparative advantage. While the assumption of quicker jobfinding is supported by existing empirical evidence, see e.g. Holzer (1988), it is useful to check it with our data. We do so by computing whether workers who found jobs through social contacts show lower duration in the unemployment spell preceding the current job.
Lastly, one of the implications of Proposition 2 is that, as social network intensity increases, the degree of mismatch also increases, so that the average worker’s productivity falls. This is an aggregate effect implying that regions or countries where workers find jobs through social contacts more often should also have lower average wages, which is tested below.

8 Data and empirical results

8.1 Proposition 1: Average wage discount on network jobs

To test Proposition 1 we use US data from the "Multi-City Study of Urban Inequality, 1992-1994" (MCSUI). This is a survey carried out by the Inter-University Consortium for Political and Social Research over those 3 years in four major US cities, Atlanta, Boston, Detroit, and Los Angeles (different periods in each city). Its purpose was to investigate the interaction of labor market dynamics, attitudes towards race and towards inequality, and racial residential segregation in generating urban inequality; see Bobo et al. (2000). It contains both a household and an employer survey, of which we shall only be using the former.

The total sample size is 8,916 but, for various reasons, our sample is reduced to about one-tenth of the original size. In particular, questions about jobfinding methods, which are key to our aims, were not asked in Detroit, which reduces the sample to 7,373 observations, and in the other three cities they were asked only to 3,460 people. Of those observations, 2,867 have reliable wage data and when we restrict the sample only to those employed, on temporary layoff or on sickness/maternity leave—to maximize reliability of the data by retaining only those with a recent attachment to the labor force—we are left with 1,066 observations. Lastly, restricting the sample to people with information on one of our instrumental variables (older siblings, see below) who are employees (rather than self-employed) brings down the sample size to 891 (886 when industry dummies are included).

Our first step is to ascertain whether there is any difference, on average, between the wage obtained by workers employed in jobs obtained through contacts and those obtained by other means. In our data, those employed were asked about their present job and those unemployed about their last job. We construct the Network variable from their replies to the following question:

\[ \text{Did you find your (last/present) job through friends or relatives, other people, newspaper ads, or some other way?} \]

We observe the following possible answers: (1) Friends or relatives. (2) Other persons. (3) Newspaper ads. (4) Other. (5) Refused/Don’t know/Missing. We
construct $\text{Network}$ as a dummy taking the value 1 if the reply is (1) and 0 if it is (2) through (4).

We are thus departing from the theoretical model in that we use data on jobs found through social networks rather than on search through networks. We deem the former information as more reliable for our purposes since it reveals the actual effectiveness of networks, while the available information on the latter allows for many non-exclusive methods of search and there is no information on either effort or hours devoted to each. In what follows we shall nevertheless refer to network use and network jobfinding as equivalent.

The dependent variable is the pre-tax hourly wage, including tips and bonuses. We present two specifications for our wage equation. The first one starts by including the traditional Mincer regressors, years of formal education ($\text{Schooling}$) and labor market experience ($\text{Experience}$) (computed as current age minus the age at which the person first left full-time schooling and was not in school for 16 months or more). We also tried with experience squared but it was never significant and so we exclude it from all regressions. It also contains additional controls which, depending on the theoretical model espoused, could be capturing either productivity differences or else some sort of discrimination. More specifically, we add a set of race dummies, White, Black, and Asian, leaving Hispanics and Native Americans as the excluded category; a dummy equal to 1 for Males; one for having been US born, one for working at a Small firm, defined as having less than 100 employees, and industry dummies. In the second specification we add occupation dummies.

In our total sample of employees with an observed wage (2583 observations), 48.9% found their job through a friend or a relative, whereas in the more restricted sample used for the regressions (891 observations), the corresponding number is 49.6%.

Table 1 shows a few important characteristics of workers in our sample, for both those who did not and who did find their job through networks. The latter are slightly younger, less educated but more experienced, more likely to be male and less likely to be married, white, black or Asian rather than Hispanic or Native Americans, and to have been born in the US, and they tend to have more siblings. They also tend to work more in small firms.

Many of these differences in means are quite small. However, the table also shows

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6 We also check this classification using the answers to the following separate question: Which of the following best describes your relationship to the one person who most directly helped you get your (last/current) job?: (1) Relative. (2) Friend. (3) Acquaintance. (4) Someone else. (5) Refused/Don’t know/Missing. We assign to $\text{Network}$ those responding either (1) or (2).

7 It is computed as the total amount divided by the reported number of hours. The survey flags possible data entry errors, when the computed wage is greater than $50 per hour and not reasonable based on the respondent’s occupation, or it is less than $2 per hour. We have set those values to missing.

8 The estimates presented below are similar to those obtained when we use 25 or 50 employees as the size threshold or if we use firm size and its square as regressors.
that hourly wages for those who found a job through networks are 19.4% lower than for those who did not. After controlling only for the city (which also controls for the survey period), the (log) wage difference raises to -20.7%. As Table 2 shows, once we add the above-mentioned controls the discount falls to -7.6%, and further to -6% if we add occupation dummies. This discount, which is both economically and statistically significant, provides the first piece of evidence consistent with the theory.

Since a large fraction of the literature has focused on firms using referrals from their own employees, in Table 2 we also show the estimates of the OLS wage equation adding the interaction of Network with a dummy variable indicating whether the friend or relative who helped the worker find his/her job worked for the firm by which he/she was hired (Insider). The last two columns of the table show that this interaction attracts a positive sign, as one would expect from the literature, but it is not significant. Moreover, the coefficient on Network is still significant and increases in size.

8.1.1 Determinants of network jobfinding

In order to estimate the selection-into-network-jobs equation which is part of the model, we use a set of linear probability models of the Network dummy on the same set of individual characteristics as in the wage model above.

The results appear in Table 3. First, as indicated before, more schooling leads to less use of networks. This makes sense in terms of the model, since more educated workers will tend to reap larger gains from their comparative advantage. Secondly, experience shows a negative relationship with networks, but it is not statistically significant. The model remains silent on this effect, but we expect workers to gain access to employment through other means once they have been in the labor market for a while. On the other hand, Hispanics and Native Americans (the residual category) and the non-US born appear to use networks more than other groups, as well as people working for small firms. Males and females seem to behave similarly, however. Lastly, different industries do not seem to show significantly different network activity, whereas different occupations do.

8.1.2 Instrumental variable estimates

As explained above, one approach to selection models is find an instrumental variable (IV) providing exogenous variation across network users and non-users. To test our theory, the IV should be a measure of the stock of contacts. For instance, as an extreme case, an orphan without any siblings or relatives would be less likely to have access to social networks than a person whose parents are alive and who has many siblings or relatives already in the job market.

Thinking along these lines, we use as a first instrumental variable the number of
older Siblings of the individual. It is clearly exogenous. We also think it is unlikely to affect a worker’s productivity directly, although it could be that parents devote less time to each child the higher the number of siblings, and, in that case, we would expect an even lower wage once we project on the instrument. What is interesting from our point of view is that the higher the number of siblings, the more likely is a worker to learn about jobs through relatives and friends. However, we do not expect this variable to have a linear effect, and so we cap it at 5 (i.e., it takes the value 5 for 5 or more siblings). The results for the first stage of the IV regression are shown in the last three columns of Table 3. The instrument is significantly correlated with Network in both specifications.

As a second instrumental variable we use the employment rate in the US State where the worker lived when he was 16 years old. This follows Topa’s (2000) finding that the most valuable social contacts to find a job are those with employed people, which implies that social network intensity should be positively related to the employment rate of the location. The survey provides information on the State of residence at the age of 16, which may be close to the time of labor market entry. A small number of workers were outside the US at that age. We use national labor force survey data for those people, but include an interaction of the employment rate with a dummy for the foreign country of residence to control for potential differences in survey methods (see Appendix 2). In our data, the employment rate turns out to be correlated with Network, so that it satisfies one of the conditions for a valid instrument [Table forthcoming].

The first panel of Table 4 shows that, when instrumented to correct for self-selection, the Network discount falls in absolute value (sometimes becoming a premium) and, more importantly, completely loses statistical significance. This is true regardless of the specific instrument, and more so if occupation dummies are included. As before, to check the validity of our story against the literature on employee referrals, we also estimated a specification which included an interaction between Network and Insider, using the two instruments available. Again, neither Network nor its interaction with Insider were significant.

It can be argued that the years of schooling should be treated as an endogenous variable. Available and potentially good instrumental variables are the years of schooling of the worker’s father and mother. Indeed, these variables turn out to be positively correlated with the worker’s years of schooling in our sample [Table forthcoming]. Thus, to check the robustness of our results to this variation, the bottom panel in Table 4 includes estimates of the coefficient on Network when both this variable and Schooling are instrumented with the parents’ education and either the number of older siblings or the State employment rate. While the discount now becomes a large premium, no coefficient is close to statistical significance.
8.2 Do social contacts help find jobs?

We now search for evidence regarding our assumption that social contacts help find jobs, by computing whether workers who found jobs through social contacts show lower duration in the unemployment spell preceding the current job than those who did not.

The US data from the MCSUI do not allow us to carry out this estimation, because the sample of workers who were asked the duration question is too small. For this reason, we resort to the European Community Household Panel (ECHP). This is a survey undertaken in all 15 European Union member countries. We use the waves for 1994 to 1998 (data for only 12 countries exist up to 1995). The survey provides information on personal characteristics and a similar question on finding jobs through friends and relatives to the one available for the US.

Also due to its larger size, and contrary to the US database, the ECHP allows us to get closer to the target population of the model, namely young workers choosing an occupation. For this reason, we restrict the sample to workers aged 15 to 30 years old, who are observed in their first permanent job. [Descriptive statistics forthcoming]

Table 5 presents the estimates of the (OLS) network discount with these data. The dependent variable is again the (log) hourly wage in US dollars.9 Similarly to the US, the equation includes as controls schooling dummies, experience, experience squared (absent in the US case), a gender dummy, a dummy for being born in the country of residence, a dummy for working for a small firm, industry dummies, and, in a second specification, occupation dummies. To control for wage level differences over time and space, we also include a full set of year and country dummies. The table shows that the wage discount is also present in European countries, and its magnitude, around 6%, is also similar to that found in the US. Unfortunately, due to the lack of appropriate variables, we cannot perform the IV estimation presented for the US case.

The second panel of Table 5 shows the effect of Network on the length of the preceding unemployment spell.10 It shows that workers who found jobs through social contacts spent, on average, about one month less than those who did not, implying that the basic unemployment duration-wage tradeoff in the model is consistent with the data.

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9 To minimize measurement error, we dropped observations with a monthly wage below 100 dollars and an hourly wage below 1 dollar.

10 To get closer to the model, we restrict observations to those with some unemployment in the preceding period (i.e. we aim at discarding job-to-job movements). Also, since unemployment durations were clearly grouped after 27 months, we drop observations above that value.
8.3 Proposition 2: The aggregate effects of social contacts

Lastly, we wish to test the implication that as social network intensity increases the degree of mismatch also increases, leading to lower average worker productivity falls. This is an aggregate effect implying that regions or countries where workers find jobs through social contacts more often should have lower average wages.

The European database provides data for 49 regions (amounting to 226 observations, because not all regions are present every year), and so we run a regression on average regional hourly wages and the average regional values of the controls included in the wage regressions in Table 5. The network discount in such regression is shown in Table 6, which ranges from 19\% to 38\%. These preliminary estimates appear to be too large, and we lose significance when occupation dummies are included. Nevertheless, we see them as prima facie evidence indicating that the aggregate effect of social networks is larger than the individual effect.

9 Conclusions

It is well known that friends and relatives are often a source of useful information in finding jobs. Previous research has analyzed the positive effects of these social networks in the probability of matching workers with jobs. In this paper we highlight another effect of social networks, namely that their availability may lead workers to choose occupations in which their comparative advantage is not fully exploited, because jobs in these occupations are found more easily.

We have shown with both US and European country data that there is indeed a wage discount for jobs found through networks, of around 6\%-7\%, and that modeling the selection into those jobs through a variable that captures workers’ endowment of contacts renders the discount non-significant. We have also found evidence for Europe that the presence of the tradeoff between quicker jobfinding and lower wages is present in European countries. And, lastly, for European regions we also document that there is probably an aggregate negative productivity effect of social contacts, through mismatch.

As to further research, on the theoretical front, we wish to explore why mismatch and lack of mobility can make it particularly difficult to innovate, if new innovating firms are difficult to contact or not very well connected. The growth process may suffer because workers do not want to incur the unemployment risk required to contact these new firms.

In the empirical area, it would be interesting to explore whether the wage discount applies more to workers at the beginning of their careers and then it partly fades or whether, on the contrary, networks have a permanent effect on workers’ returns to labor.
Appendix 1. Further theoretical results

Comparative statics on $M$

Partial derivative of $M$ with respect to $\eta$ From deriving $M$ with respect to $\eta$ it follows that

$$\frac{\partial M(\mu_*)}{\partial \eta} = \frac{m f - [M(\mu_*) - 1][f + (1-f)\mu_*]}{U}$$

(21)

which after rearranging yields

$$\frac{\partial M(\mu_*)}{\partial \eta} = \frac{m \phi(1-f)\mu_* [1-f\mu_* - (1-f)(\mu_*^2)]}{2 [\phi + \eta f + \eta(1-f)\mu_*]^2}.$$  

(22)

that is negative since $\mu_*$ is a quantity between zero and one.

Partial derivative of $M$ with respect to $\mu_*$ Deriving $M$ with respect to $\mu_*$ yields

$$\frac{\partial M(\mu_*)}{\partial \mu_*} = -(1-f)m \phi \mu_* + \eta [M(\mu_*) - 1] \phi + \eta f + \eta(1-f)\mu_*$$

which after using (OC) and the definition of $U$ reads as

$$\frac{\partial M(\mu_*)}{\partial \mu_*} = -\eta(1-f)M(\mu_*)$$

(23)

which is negative.

Partial derivative of $M$ with respect to $\phi$ Deriving $M$ with respect to $\phi$, and after rearranging, yields

$$\frac{\partial M(\mu_*)}{\partial \phi} = \frac{m \eta(1-f)\mu_* [1-\mu_* [f + (1-f)\mu_*]]}{2 [\phi + \eta f + \eta(1-f)\mu_*]^2}$$

which is clearly positive.

OC’ has unique solution increasing in the $\eta/m\phi$ ratio It follows from $\alpha < 2/(2+m)$ that the right-hand side of (OC’) at $\mu_* = 0$, is always positive. As the right hand side of (OC’) is a continuous non decreasing function of $\mu_*$ mapping the $[0,1]$ interval into itself, it follows from Brouwer fixed point theorem that a solution
to (OC') always exists. Furthermore, following the same steps as those that led to (23) we can show that at any point (if any) where \( \mu_* \) is equal to \( \frac{\eta m}{\phi} [1 - \alpha M(\mu_*)] \)

\[
\frac{\partial M(\mu_*)}{\partial \mu_*} = -\frac{\eta(1 - f)(1 - \alpha)M(\mu_*)}{\phi + \eta f + \eta(1 - f)\mu_*}
\]

(24)

which is not only negative but also increasing. But then, since \( \frac{\eta m}{\phi} [1 - \alpha M(0)] \) is strictly positive at \( \mu_* \) equal to zero, it follows that the \( \frac{\eta m}{\phi} [1 - \alpha M(\mu_*)] \) line can cross the 45 degree line at most once from above to below. This intersection exists if and only \( \frac{\eta m}{\phi} [1 - \alpha M(1)] < 1 \) which implies that \( \mu_* \) equal to one is not a solution to (OC'). Alternatively, the only solution to (OC') features \( \mu_* \) equal to one which concludes the proof.

To see that solution to (OC') is increasing in the \( \eta/m\phi \) ratio simply notice that the right hand side of (OC') is increasing in \( \mu_* \) and that an increase in such a ratio raises the right hand side of (OC') for any value of \( \mu_* \).

Welfare results

The derivative \( \frac{dW}{d\eta}|_{FB} \) is always positive At the first best allocation, the envelope theorem guarantees that \( \frac{dW}{d\eta} = \frac{\partial W}{\partial \eta} \). But then partial derivation with respect to \( \eta \) in (10) and after using (11) yields

\[
\frac{\partial W}{\partial \eta} = 2 [f + (1 - f)\mu_*] \frac{\gamma(\theta_s)c\theta_s}{1 - \gamma(\theta_s)} + 2Up(\theta_s)y\frac{\partial M}{\partial \eta}.
\]

(25)

Notice that this derivative is clearly positive when \( \mu_* \) is either equal to zero or one since it follows from (22) that, for these values of \( \mu_* \), \( \frac{\partial M}{\partial \eta} \) is always equal to zero. It then remains to analyze the case where \( \mu_* \) is strictly between zero and one. for this values. In that case it follows from (12) that \( \mu_* = \frac{\eta}{\sigma m} \{1 - \gamma(\theta_s)\} M(\mu_*) \} < 1 \). By using (21) to substitute for \( \frac{\partial M}{\partial \eta} \) in (25) and after using (11) to substitute for \( p(\theta_s)y \) it follows that

\[
\frac{\partial W}{\partial \eta} = 2 \frac{[f + (1 - f)\mu_*] c\theta_s}{[1 - \gamma(\theta_s)] M(\mu_*)} \{1 - \gamma(\theta_s)\} M(\mu_*)} + 2p(\theta_s)y \frac{m}{2} f
\]

which under the maintained assumption that \( \mu_* \) is less than one it is clearly positive.

Evaluation of \( \frac{d\ln W}{d\eta}|_{EQ} \) in some specific cases After using (23), (21), and (OC) to calculate the total derivative of \( M \) with respect to \( \mu_* \) it follows that

\[
\frac{dM(\mu_*)}{d\eta} = \frac{m}{2} f + f + (1 - f)\mu_* - M(\mu_*) \frac{[f + 2(1 - f)\mu_*]}{U}.
\]
Then after calculating the total derivative of $U$ with respect to $\eta$ and evaluating (14) it follows that $\frac{d \ln W}{d \eta} \bigg|_{\text{EQ}}$ is negative if and only if the following inequality holds

$$[1 - \gamma(\theta)] [f + 2(1 - f)\mu_*] M(\mu_*) > \left(1 + \frac{m}{2}\right) f + (1 - f)\mu_*.$$

By evaluating this inequality for different values of the parameter and after remembering the definition of $M(\mu_*)$, it immediately follows that

1. If $\gamma(\theta)$ is equal to zero, $\frac{d \ln W}{d \eta} \bigg|_{\text{EQ}}$ is negative.

2. When $\eta = \phi m$ (so that $\mu_* = 1$), $\frac{d \ln W}{d \eta} \bigg|_{\text{EQ}}$ is negative, if and only if $(1 - \bar{\gamma})(2 - f) > 1$.

3. When either $\eta = 0$ (so that $\mu_* = 0$) or $f = 1$, $\frac{d \ln W}{d \eta} \bigg|_{\text{EQ}}$ is always positive.

### Appendix 2. Classifications and definitions

[To be completed]

**US Data**

List of industry dummies: Agriculture, forestry and fisheries; Mining; Construction; Manufacturing; Transportation, communications and other public utilities; Wholesale trade; Retail trade; Finance insurance and real estate; Business and repair services; Personel services; Entertainment and recreation services; Professional and related services; and Public administration.

List of occupation dummies: Managerial, Technical, Services, Farming, Craft, Operator.

Source for employment rate data. US: Bureau of Economic Analysis and Current Population Survey. Outside US: National surveys. There are residents in Puerto Rico, Mexico, Central America, Dominican Republic, South America, South Korea, and Hong-Kong. In the end, only the interactions for Hong-Kong and the Dominican Republic were significant and kept as instruments.

**European data**

List of industry dummies: Agriculture, Manufacturing; Services.

List of occupation dummies: High skill, Medium skill, Low skill.
References


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Table 1. Sample characteristics of US data

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<tr>
<th></th>
<th>Job found through networks</th>
<th>Job not found through networks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>std. dev.</td>
</tr>
<tr>
<td>Age</td>
<td>27.3</td>
<td>3.9</td>
</tr>
<tr>
<td>Schooling</td>
<td>12.2</td>
<td>3.0</td>
</tr>
<tr>
<td>Experience</td>
<td>8.7</td>
<td>4.7</td>
</tr>
<tr>
<td>Male</td>
<td>55.4</td>
<td>49.8</td>
</tr>
<tr>
<td>US Born</td>
<td>50.2</td>
<td>50.1</td>
</tr>
<tr>
<td>White</td>
<td>22.2</td>
<td>41.6</td>
</tr>
<tr>
<td>Black</td>
<td>26.2</td>
<td>44.1</td>
</tr>
<tr>
<td>Asian</td>
<td>6.3</td>
<td>24.4</td>
</tr>
<tr>
<td>Other race</td>
<td>45.3</td>
<td>49.8</td>
</tr>
<tr>
<td>Small firm</td>
<td>72.9</td>
<td>44.5</td>
</tr>
<tr>
<td>Siblings</td>
<td>1.9</td>
<td>1.8</td>
</tr>
<tr>
<td>No. of observ.</td>
<td>442</td>
<td></td>
</tr>
</tbody>
</table>

Note. The first three variables are in years, Siblings is a number, the remainder are percentage shares.

Table 2. The discount on network jobs in the US.

OLS wage equation

Dependent variable: log wage

<table>
<thead>
<tr>
<th>Coefficient on Network:</th>
<th>coeff.</th>
<th>t</th>
<th>Adj. R²</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>-7.57</td>
<td>(2.84)</td>
<td>0.38</td>
<td>886</td>
</tr>
<tr>
<td>With occupation dummies</td>
<td>-5.97</td>
<td>(2.27)</td>
<td>0.37</td>
<td>886</td>
</tr>
<tr>
<td>With occupation dummies and Network × Insider</td>
<td>-8.03</td>
<td>(2.03)</td>
<td>0.37</td>
<td>886</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Coefficient on Network × Insider:</th>
<th>coeff.</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2.85</td>
<td>(0.70)</td>
</tr>
</tbody>
</table>

Note. The baseline specification includes a constant, city dummies, years of schooling, experience, race dummies (white, black, asian), a gender dummy, a dummy for being born in the US, a dummy for working for a small firm, and industry dummies. See Appendix 2 for the industry and occupation classifications.
Table 3. Covariates of network jobfinding in the US

Dependent variable: *Network*

<table>
<thead>
<tr>
<th></th>
<th>coeff.</th>
<th>t</th>
<th>coeff.</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Schooling</td>
<td>-0.030</td>
<td>3.95</td>
<td>-0.021</td>
<td>2.62</td>
</tr>
<tr>
<td>Experience</td>
<td>-0.007</td>
<td>1.74</td>
<td>-0.007</td>
<td>1.69</td>
</tr>
<tr>
<td>White</td>
<td>-0.095</td>
<td>1.71</td>
<td>-0.078</td>
<td>1.40</td>
</tr>
<tr>
<td>Black</td>
<td>-0.060</td>
<td>1.13</td>
<td>-0.055</td>
<td>1.04</td>
</tr>
<tr>
<td>Asian</td>
<td>-0.199</td>
<td>3.00</td>
<td>-0.179</td>
<td>2.69</td>
</tr>
<tr>
<td>Male</td>
<td>0.048</td>
<td>1.35</td>
<td>0.030</td>
<td>0.83</td>
</tr>
<tr>
<td>US Born</td>
<td>-0.093</td>
<td>1.77</td>
<td>-0.075</td>
<td>1.59</td>
</tr>
<tr>
<td>Small firm</td>
<td>0.081</td>
<td>2.22</td>
<td>0.076</td>
<td>2.07</td>
</tr>
<tr>
<td>Siblings</td>
<td>0.023</td>
<td>2.32</td>
<td>0.022</td>
<td>2.29</td>
</tr>
<tr>
<td>Industry dummies</td>
<td>yes</td>
<td></td>
<td>yes</td>
<td></td>
</tr>
<tr>
<td>(p-value)</td>
<td>0.75</td>
<td></td>
<td>0.83</td>
<td></td>
</tr>
<tr>
<td>Occupation dummies</td>
<td>no</td>
<td></td>
<td>yes</td>
<td></td>
</tr>
<tr>
<td>(p-value)</td>
<td>–</td>
<td></td>
<td>0.07</td>
<td></td>
</tr>
</tbody>
</table>

No. obs.       | 886    |     | 886    |     |
Adj. $R^2$      | 0.48   |     | 0.48   |     |

Note. See Appendix 2 for the lists of industry and occupation dummies.
Table 4. IV wage equation and network jobfinding in the US

Dependent variable: log wage  
Coefficient on Network

<table>
<thead>
<tr>
<th></th>
<th>coeff.</th>
<th>t</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>I. Instrumenting Network:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IV: Siblings</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>1.60</td>
<td>(0.05)</td>
<td>886</td>
</tr>
<tr>
<td>With occupation dummies</td>
<td>2.40</td>
<td>(0.07)</td>
<td>886</td>
</tr>
<tr>
<td>IV: State employment rate</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>-6.02</td>
<td>(0.25)</td>
<td>801</td>
</tr>
<tr>
<td>With occupation dummies</td>
<td>-1.64</td>
<td>(0.06)</td>
<td>801</td>
</tr>
<tr>
<td><strong>II. Instrumenting Network and Schooling:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IV: Siblings and parental education</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>8.58</td>
<td>0.20</td>
<td>627</td>
</tr>
<tr>
<td>With occupation dummies</td>
<td>10.36</td>
<td>0.25</td>
<td>627</td>
</tr>
<tr>
<td>IV: State employment rate and parental education</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>10.11</td>
<td>0.33</td>
<td>625</td>
</tr>
<tr>
<td>With occupation dummies</td>
<td>18.67</td>
<td>0.56</td>
<td>625</td>
</tr>
</tbody>
</table>

Note. The baseline specification includes a constant, city dummies, years of schooling, experience, race dummies (white, black, asian), a gender dummy, a dummy for being born in the US, a dummy for working for a small firm, and industry dummies. Where indicated, they also include occupation dummies. See Appendix 2 for the industry and occupation classifications.
Table 5. The tradeoff: wages and unemployment duration in Europe

<table>
<thead>
<tr>
<th></th>
<th>coeff.</th>
<th>t</th>
<th>Adj. R²</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>II. The discount on network jobs</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dependent variable: log wage</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coefficient on Network:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>-6.72</td>
<td>(2.85)</td>
<td>0.52</td>
<td>1802</td>
</tr>
<tr>
<td>With occupation dummies</td>
<td>-6.00</td>
<td>(2.61)</td>
<td>0.54</td>
<td>1772</td>
</tr>
<tr>
<td>II. The reduction in unemployment duration</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dependent variable: months of unemployment before current job</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coefficient on Network:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>-1.07</td>
<td>(2.02)</td>
<td>0.16</td>
<td>1804</td>
</tr>
<tr>
<td>With occupation dummies</td>
<td>-1.10</td>
<td>(2.08)</td>
<td>0.17</td>
<td>1774</td>
</tr>
</tbody>
</table>

Note. Both equations are estimated by OLS. The baseline specification includes a constant, year and country dummies, schooling dummies, experience, experience squared, a gender dummy, a dummy for being born in the country of residence, a dummy for working for a small firm, and industry dummies. Where indicated, they also include occupation dummies. See Appendix 2 for the industry and occupation classification.

Table 6. The aggregate network discount in Europe

<table>
<thead>
<tr>
<th></th>
<th>coeff.</th>
<th>t</th>
<th>Adj. R²</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>-32.78</td>
<td>(2.02)</td>
<td>0.90</td>
<td>226</td>
</tr>
<tr>
<td>With occupation dummies</td>
<td>-18.79</td>
<td>(1.19)</td>
<td>0.91</td>
<td>226</td>
</tr>
</tbody>
</table>

Note. OLS regressions. The baseline specification includes a constant, year and country dummies, average regional experience, and regional fractions of: schooling levels, males, born in the country of residence, working for a small firm, and working by industry. See Appendix 2 for the industry and occupation classifications.