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Endogenous Job Contact Networks*

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Abstract

We develop a model where workers, anticipating the risk of becoming unemployed, invest in connections in order to access information about available jobs that other workers may have. The investment in connections is high when the job separation rate in the labor market is moderate, whereas it is low for either low or high levels of job separation rate. The equilibrium response of network investment to changes in the labor market conditions generates novel empirical predictions. In particular, the probability that a worker finds a new job via his connections increases in the separation rate when the separation rate is low, while it decreases when the separation rate is high. These predictions are supported by the empirical patterns that we document for the UK labor market.

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1. Introduction

It is well established that job contact networks play a prominent role in matching workers with vacant jobs. Empirical work, starting with Rees (1966) and Granovetter (1973), shows that between 30 percent and 50 percent of jobs are filled through the use of social networks. The findings of Granovetter (1973) and Rees (1966) have been generalized across countries, industrial sectors and demographic characteristics, see for example, Blau and Robins (1990), Topa (2001), Munshi (2003), Loury (2006), Bayer, et al. (2008), Cappellari and Tatsiramos (2010), and Cingano and Rosolia (2012).² The evidence that many workers become aware of available jobs through word-of-mouth has led to a number of theoretical studies, which explore the importance of social networks for labor market outcomes. For example, Boorman (1975), Mortensen and Vishwanath (1994), Arrow and Borzekowski (2004), Calvó-Armengol (2004), Calvó-Armengol and Jackson (2004, 2007), Calvó-Armengol and Zenou (2005), Fontaine (2007), and Cahuc and Fontaine (2009).

Most of this work assumes that the intensity of information flow in the network is exogenous, an assumption that prevents the study of how incentives in networking relate to different labor market conditions. As the process of forming connections and keeping them active requires time and effort, it is natural to posit that the resources that an individual spends in searching via his network are, at least in part, the result of cost and benefit analysis. This paper investigates, theoretically and empirically, the nature of the feedback between labor market conditions and the role of social networks in matching vacancies with job seekers.

Our first contribution is to develop a simple model of the decision of workers to invest in network contacts for job finding. Workers invest in connections with the view of accessing information about new jobs that other workers may have. A particular role played by connections is that they partially insure workers against the risk of unemployment, which is higher when the job separation rate is higher. Hence, individuals' incentives to invest in the network depend on the labor market conditions. This interplay generates a set of novel comparative statics results, which we now illustrate.

²See Ioannides and Loury (2004) for an exhaustive survey on social networks and labor market.

When the job separation rate is low, a worker does not invest much in the network because the risk of unemployment is low. When the job separation rate is high, workers will not invest much in connections because they anticipate that workers with whom they interact are either most likely looking for a job as well or are in contact with many workers who need their referral. So, workers' investment in searching via the network is pronounced when there is a moderate separation rate in the labor market. The main result of the paper is to show that this inverted *U*-shape relation between job separation rate and network investment determines an inverted *U*-shape relation between job separation rate and the probability of a worker to find a job via his social contacts, which we term network matching rate.

The non-monotonic relation between job separation rate and network matching rate is novel and important. It is not consistent with the predictions of existing work, which assumes that the intensity with which individuals look for jobs through their networks is exogenous. Furthermore, such equilibrium relation has the implication that, in times of turbulence, individuals who rely on social connections more than average, such as unskilled workers, young job seekers, ethnic minorities and immigrants, will be more adversely affected by negative shocks.

We have derived these predictions in a static labor market model with exogenous vacancy rate. In our theoretical analysis, we extend the model to a dynamic setting. The network is formed initially and then the dynamics of a labor market with free entry of firms à la Pissarides (2000) unravels. After deriving formally the conditions for equilibrium, we provide a numerical exercise that confirms the robustness of the mechanisms underlying our basic model.

Our second contribution is to document how network investment and network matching rate respond to changes in the probability of entering into unemployment. We study the labor market outcomes of workers using the UK Quarterly Labour Force Survey (QLFS) over the period from 1994 to 2005. In this survey, respondents looking for a job were asked about their main job search method. This information allows us to determine the proportion of job seekers, in a given region, that reported to use friends, relatives and colleagues as a main job search method in each period. This is our proxy for network investment. Furthermore, in the survey, respondents who found a job in the three months previous to the interview were asked how they found their current position. This

information allows us to construct the proportion of workers that, in each region, reported to have found their new job by “hearing from someone who worked there”. This is our proxy for network matching rate.

Using the information in the survey on respondents’ region of residence, we investigate regional differences in network investment in job search and in the network matching rate. We first calculate our proxies of network investment and network matching rate at a yearly frequency. We then regress each of these variables against the yearly averages of the job separation rate, also constructed at the regional level. In line with our theoretical predictions, we find that the effect of the job separation rate on network investment, and on network matching rate, is positive and concave. Nonetheless, when labor market conditions deteriorate, the relationship becomes negative.

These empirical findings are robust to the inclusion of time dummies and to longer time spans of aggregation of the data (five-year average). This assures us that the relationship between network investment and network matching rate with job separation rate are not driven by time trends in the data. The findings are also robust to a further disaggregation of the data based on workers’ educational attainment, a proxy for workers’ skills. The results of this last exercise show that, in line with our model, a worsening of labor market conditions may reduce the effectiveness of networks in job search for low skilled workers, who are the ones relying more on networks in the first place. In this sense, low skilled workers become even more vulnerable in downturns.

Our paper contributes to the literature of network referrals in labor markets. Most of the literature on labor market and social networks assumes that the use of job contact networks is exogenous to labor market conditions. Notable exceptions are Boorman (1975) and Calvó-Armengol (2004).³ Boorman (1975) is the first to provide a model that integrates social networks with labor markets and his focus is on workers’ incentives to form weak *versus* strong ties. Calvó-Armengol (2004) provides a characterization of stable job contact networks in a two-sided link formation model of the type introduced by Jackson and Wolinsky (1996). Our model is complementary to this earlier work.

³The theory of network formation is a recent but very active field of study. For a survey of this research, see Goyal (2007) and Jackson (2008). Complex random networks have also received large attention in economics, for example, Cabrales, Calvó-Armengol and Zenou (2011) and Galeotti, et al. (2010); for a survey see Vega-Redondo (2007).

While we do not focus on the specific details of the architecture of equilibrium job contact networks, we explore how labor market conditions affect the use of social networks and their effectiveness in matching job seekers to vacancies. To the best of our knowledge, our paper is the first to analyze these questions systematically.

Montgomery (1991) and, more recently, Galenianos (2012), study another role of job contact networks: to transmit information about the quality of workers. We abstract from the effects that connections may have in alleviating asymmetric information between firms and workers, and focus on the role of connections in spreading information about job opportunities. More importantly, in our model, the use of social networks is endogenous, an ingredient that gives rise to new implications and empirical predictions.

Our work also relates to the labor market literature with endogenous search effort pioneered by Diamond (1982). For recent surveys, see Mortensen and Pissarides (1999) and Pissarides (2000). From this literature we borrow the idea that search units are chosen optimally to maximize the net returns from search, and we apply it to the formation of job contact networks. We then derive a micro-founded matching function where the number of matchings between workers and vacancies depends on the average connectivity of the endogenous job contact network.

2. Model

We develop a simple model of the decision of workers to invest in network contacts for job finding. In the model, the benefit to a worker of forming connections is the increase in the probability to find a job when needed; the cost is the effort invested in building and maintaining such connections. Since the necessity of a worker to rely on his connections to find an occupation depends on market conditions, the equilibrium outcome provides predictions on how labor market conditions affect the formation of the job contact network and, consequently, the network matching rate.

The basic model is static and wage and vacancy rate are both exogenous. Due to the simplicity of this model, our analytical results, presented in Section 3, cleanly highlight how a change in some fundamentals of the labor market affects the incentives of workers to invest in larger or smaller

networks, and the resulting network matching rate. At the end of Section 3, we shall consider a dynamic version of our model, where the network is formed initially and then a standard labor market dynamics unravels. We derive the equilibrium condition of network investment in this steady state model where vacancy rate is endogenous. We then provide numerical evidence that the basic mechanisms derived in the static model are robust.

The model has three building blocks: labor market turnover, information diffusion within the network, and formation of job contact networks. There is a large set of risk neutral workers $\mathcal{N} = \{1, \dots, n\}$. Initially all workers are employed and earn an exogenous wage that, without loss of generality, is normalized to 1.

Labor Market Turnover. Two exogenous parameters govern the labor market turnover.

Job loss. A randomly selected sample of size $B = \delta n > 1$ of workers become unemployed, where $\delta \in (0, 1) \cap \mathbb{Q}$ is the job separation rate. We denote by $\mathcal{B} \subset \mathcal{N}$ the set of workers who lose their job and we call them *job seekers*.

Job opening. A number $V = an$ of new vacancies opens in the market, where $a \in (0, 1] \cap \mathbb{Q}$ is the vacancy rate. These vacant jobs are distributed to workers in the following way: δV vacancies reach a randomly selected sample of job seekers, and the remaining vacancies reach a randomly selected sample of workers who did not lose their job. Let $\mathcal{A} \subset \mathcal{N}$ be the set of workers who receive a direct job offer.

Under this protocol, nobody receives more than one direct job offer. The set $\mathcal{U} = \mathcal{B} \cap \{\mathcal{N} \setminus \mathcal{A}\}$ is the set of workers who have lost their job and did not receive a direct offer; note that $|\mathcal{U}| = \delta(1-a)n$. The set $\mathcal{O} = \mathcal{A} \cap \{\mathcal{N} \setminus \mathcal{B}\}$ contains workers who have not lost their job and received a direct offer. We say that a worker $i \in \mathcal{O}$ has a *needless offer* and we note that there are $|\mathcal{O}| = a(1-\delta)n$ needless offers.

Ex-ante, a representative worker anticipates that with probability $\delta(1-a)$ he will be unemployed and without a new offer. In that case, he earns an unemployment benefit which, without loss of generality, is normalized to 0. In order to insure themselves against this risk, workers invest in social connections with the view of accessing needless offers.

Job Contact Network. We specify the network formation game below. For the moment, let

us assume that workers are located in an undirected network g . A link between workers i and j is denoted by $g_{ij} = 1$, while $g_{ij} = 0$ means that i and j are not linked. The set of all possible undirected networks is \mathcal{G} . With some abuse of notation, we denote the set of i 's neighbors belonging to $\mathcal{V} \subset \mathcal{N}$ in network g as $\mathcal{N}_i(\mathcal{V}) = \{j \in \mathcal{V} \setminus \{i\} : g_{ij} = 1\}$; $\eta_i(\mathcal{V}) = |\mathcal{N}_i(\mathcal{V})|$ is the number of links that i has with workers belonging to \mathcal{V} .

Job transmission in the network. We assume that information about jobs flows only from workers with a needless offer to job seekers.⁴ Formally, each $i \in \mathcal{O}$ passes the information to one and only one $j \in \mathcal{N}_i(\mathcal{B})$, chosen at random. If i is not linked to any job seeker, i.e., $\mathcal{N}_i(\mathcal{B})$ is the empty set, the offer is lost.⁵

Formation of job contact networks. The protocol of network formation follows Cabrales, et al. (2011). We consider the following simultaneous network formation game. Each worker i chooses a costly network investment $s_i \geq 0$; the marginal cost of a unit of investment is constant and equal to c .⁶ The set of pure strategies available to worker i is $\mathcal{S}_i = \mathbb{R}_+$. A pure strategy profile is $\mathbf{s} = (s_1, \dots, s_n) \in \mathcal{S} = \mathbb{R}_+^n$, and \mathbf{s}_{-i} indicates the strategies of all workers other than worker i . We denote by $y(\mathbf{s}) = \sum_{i \in \mathcal{N}} s_i$ the aggregate workers' network investment. For a profile \mathbf{s} , we assume

⁴We are assuming that information only flows one-step in the network. As it is shown in Appendix A.2, this assumption is not important for our results.

⁵We are assuming that a worker passes a needless offer to one of his social contacts, chosen at random. The implication of this assumption is that two job seekers, both connected to a worker with a needless offer, “compete” for such offer. If a worker with a needless offer is allowed to give it to both job seekers, then they will have an identical offer and therefore competition for the job will still be present in the hiring process (given that one job offer corresponds to one vacancy).

⁶All the results we present can be derived with arbitrary cost functions $C(s)$ that are increasing and convex in s .

that a link between an arbitrary pair of workers i and j forms with probability⁷

$$(1) \quad \Pr(g_{ij} = 1 | \mathbf{s}) = \begin{cases} \min\left\{\frac{s_i s_j}{y(\mathbf{s})}, 1\right\} & \text{if } y(\mathbf{s}) > 0, \\ 0 & \text{otherwise.} \end{cases}$$

A profile \mathbf{s} generates a multinomial random graph. When workers choose the same level of investment, say s , the induced random graph is binomial, the probability that two workers are connected equals the per-capita network investment, $\min\{s/n, 1\}$, and the average connectivity of the random graph (the expected number of neighbors of a node) is $\min\{s/n, 1\}(n - 1)$.⁸

Interpretation of the model of network formation. There are two complementary interpretations of the process of network formation that we have formalized. The first interpretation is that network investment reflects the time that an individual spends in organizations, clubs, conferences, churches, etc. An individual who participates in many organizations has greater chances to meet other people and form connections with them. In turn, these connections may provide valuable information about job opportunities. The second interpretation is that individuals are connected in a pre-existing network. For example, we may think of a group of immigrants living in the same neighborhood and define the pre-existing network by geographical proximity. This is the assumption behind the approach of Topa (2001), which finds a significantly positive amount of social interactions within neighborhoods. While the existence of such a link (for example, living in closed proximity) is a necessary condition for information exchange, it is not sufficient: for the information to flow from one individual to another, their communication links must be active, which requires investment from both workers. In this case, workers' network investment determines the strength of each pre-existing

⁷Expression (1) can be derived by requiring three axioms on network formation. These axioms are: *one*, undirected links, i.e., $\Pr(g_{ij} = 1 | \mathbf{s}) = \Pr(g_{ji} = 1 | \mathbf{s})$; *two*, aggregate constant returns to scale, i.e., for all $i \in \mathcal{N}$, $\sum_{j=1}^n \Pr(g_{ij} = 1 | \mathbf{s}) = s_i$; and *three*, anonymous link formation, i.e., for all $j, l \in \mathcal{N}$, $\Pr(g_{ji} = 1 | \mathbf{s})/s_j = \Pr(g_{li} = 1 | \mathbf{s})/s_l$, for all $i \in \mathcal{N} \setminus \{j, l\}$. See Cabrales, et al. (2011) for details.

⁸We refer to Erdos and Renyi (1959) for a study of binomial random graphs, and to Chung and Lu (2002) for a study of multinomial random graphs. Vega-Redondo (2007) and Jackson (2008) provide a detailed overview of the rapidly growing literature on complex networks.

link in the community.

Utilities and Equilibrium. For a strategy profile $\mathbf{s} = (s_i, \mathbf{s}_{-i})$, let $\Psi_i(\mathbf{s})$ be the probability that worker $i \in \mathcal{B}$ accesses at least one offer from the network, which we shall refer to as i 's network matching rate and that we will derive in the next section. The expected utility to a worker $i \in \mathcal{N}$ is:

$$(2) \quad EU_i(s_i, \mathbf{s}_{-i}) = 1 - \delta(1 - a)[1 - \Psi_i(\mathbf{s})] - cs_i.$$

The last term represents the cost of investment in the network and the first part is the probability that worker i will be employed and therefore earning a wage equal to 1. This is the complement of the probability that worker i is a job seeker and he neither accesses a direct offer nor information from the network.

A pure strategy equilibrium is \mathbf{s} such that, for all $i \in \mathcal{N}$,

$$EU_i(s_i, \mathbf{s}_{-i}) \geq EU_i(s'_i, \mathbf{s}_{-i}), \forall s'_i \in \mathcal{S}_i.$$

We focus on pure strategy symmetric equilibrium in large labor markets, hereafter equilibrium. A large labor market is a labor market in which $n \rightarrow \infty$. Note that, by definition, $B/n = \delta$ and $V/n = a$.⁹

3. Analysis

We first consider the case where the job contact network is given and we explicitly derive the network matching rate. We then derive the equilibrium network and provide comparative statics result. All proofs of the analytical results are in Appendix A.1.

⁹We present the analysis for large labor markets. However, our results can be easily extended to an environment with a finite and sufficiently large n .

3.1. Exogenous job-contact network

For simplicity, we focus on networks generated by a symmetric profile of network investment, i.e., $s_i = s$ for all $i \in \mathcal{N}$. We recall that a symmetric profile of investments generates a binomial random graph, which in a large labor market coincides with a Poisson random graph. Since all offers are identical, the probability that an arbitrary job seeker $i \in \mathcal{B}$ finds a job—the *matching rate*—is given by $m(s) = a + (1 - a)\Psi(s)$. We now derive the network matching rate $\Psi(s)$.

The probability that $i \in \mathcal{B}$ has η links with workers who have a needless offer is $\Pr(\eta_i(\mathcal{O}) = \eta) = B(\eta|p, |\mathcal{O}|)$, where $B(\cdot|p, |\mathcal{O}|)$ is the binomial distribution, $p = s/n$ is the probability of a success and $|\mathcal{O}|$ is the number of trials. Let j be an arbitrary i 's neighbor with a needless offer, i.e., $j \in \mathcal{N}_i(\mathcal{O})$. The probability that j is connected to ω job seekers (given that he is already linked to i) is simply:

$$\Pr(\eta_j(\mathcal{B}) = \omega | g_{ij} = 1) = B(\eta - 1|p, |\mathcal{B}| - 1),$$

and the probability that j passes the job information to i is $1/\omega$. So, the expected probability that the connection to j results in a job information to i is:

$$\sum_{\omega=1}^{|\mathcal{B}|} \Pr(\eta_j(\mathcal{B}) = \omega | g_{ij} = 1) \frac{1}{\omega}.$$

We now observe that the probability that each i 's neighbor, with a needless offer, passes the information to i is independent. Hence, if worker i has η links with workers like j , the probability that i does not hear about a new job is:

$$\left[1 - \sum_{\omega=1}^{|\mathcal{B}|} \Pr(\eta_j(\mathcal{B}) = \omega | g_{ij} = 1) \frac{1}{\omega} \right]^\eta,$$

and the expected probability that $i \in \mathcal{B}$ does not get an offer via the network is:

$$(3) \quad \phi(s) = \sum_{\eta=0}^{|\mathcal{O}|} \left\{ \Pr(\eta_i(\mathcal{O}) = \eta) \left[1 - \sum_{\omega=1}^{|\mathcal{B}|} \Pr(\eta_j(\mathcal{B}) = \omega | g_{ij} = 1) \frac{1}{\omega} \right]^\eta \right\}.$$

Using $|\mathcal{B}| = \delta n$ and $|\mathcal{O}| = na(1 - \delta)$ and the binomial identity, we can rewrite (3) as follows:

$$(4) \quad \phi(s) = \left[1 - \frac{1 - (1 - p)^{n\delta}}{\delta n} \right]^{na(1-\delta)}.$$

Since $p = s/n$, in a large labor market we obtain that the network matching rate is

$$(5) \quad \Psi(s) = 1 - \lim_{n \rightarrow \infty} \phi(s) = 1 - e^{-\frac{a(1-\delta)}{\delta}(1-e^{-s\delta})}.$$

Proposition 1 Consider a large labor market and suppose that $s_i = s$ for all $i \in \mathcal{N}$. Then, the matching rate and the network matching rate are decreasing in separation rate.¹⁰

The network matching rate describes the extent to which network information transmission alleviates labor market frictions. Proposition 1 shows that, under the assumption of exogenous networks, any change in labor market conditions that decreases the number of jobs available in the network, $a(1 - \delta)$, relative to the proportion of job seekers in the network, δ , unambiguously decreases the effectiveness of the network in matching job seekers to vacancies.

3.2. Endogenous job-contact network

We now study the implication of allowing individuals to choose strategically how much to invest in the network. Given that all agents $j \neq i$ invest $s_j = s$, the problem of agent i is to choose s_i to maximize:

$$EU_i(s_i, s) = 1 - \delta(1 - a)[1 - \Psi_i(s_i, s)] - cs_i,$$

where, in a large labor market,

$$\Psi_i(s_i, s) = 1 - e^{-\frac{a(1-\delta)}{\delta} \frac{1-e^{-s\delta}}{s} s_i}.$$

The following proposition characterizes interior equilibria.¹¹

¹⁰It is easy to show that a decrease in vacancy rate has the same effects as an increase in separation rate.

¹¹We note that there always exists an equilibrium where workers do not invest in the network, i.e., $s_i = 0$ for all $i \in \mathcal{N}$.

Proposition 2 Consider a large labor market. An interior equilibrium s^* exists if, and only if, $c < a\delta(1 - a)(1 - \delta)$, and s^* is the unique solution to:

$$(6) \quad \delta(1 - a) \left[\frac{a(1 - \delta)}{\delta s^*} \left(1 - e^{-s^*\delta} \right) e^{-\frac{a(1-\delta)}{\delta}(1-e^{-s^*\delta})} \right] = c.$$

In the unique interior equilibrium, the level of network investment balances a worker's marginal returns with marginal costs. The marginal returns are the marginal increase in network matching rate (the term in square brackets), weighted by the likelihood a worker needs the network to find a job, $\delta(1 - a)$. The next result shows the equilibrium relation between job separation rate, investment in searching for jobs via the network, and the network matching rate.¹²

Proposition 3 Consider a large labor market and suppose that $c < a\delta(1 - a)(1 - \delta)$.

1. For every $a \in (0, 1)$, there exists $\bar{\delta}(a) > 0$ such that if $\delta < \bar{\delta}(a)$, then the network investment increases in the separation rate, otherwise it decreases in the separation rate.
2. For every $a \in (0, 1)$, there exist $\hat{\delta}(a) > 0$ and $\tilde{\delta}(a) \geq \hat{\delta}(a)$ such that if $\delta < \hat{\delta}(a)$, then the network matching rate increases in the separation rate, while if $\delta > \tilde{\delta}(a)$ it decreases in the separation rate.

The first part of Proposition 3 shows that the investment in the network is low when the separation rate is either low or high whereas, when the separation rate is at intermediate levels, workers invest heavily in the network. Intuitively, when the separation rate is low, there is not much value in

However, analyzing the best response dynamics after a perturbation around the equilibrium, it is possible to show that this equilibrium is unstable whenever it coexists with an interior equilibrium. Moreover, when $c \geq a\delta(1 - a)(1 - \delta)$ the equilibrium in which workers do not invest in the network is the only symmetric equilibrium. A formal proof of this statement is available upon request to the authors.

¹²We focus on separation rate because, in the dynamic model we analyze below, we will endogenize the arrival rate of offers via free entry of firms. Furthermore, we can recover the job separation rate from the data and, therefore, test the predictions of the model. We note, however, that in this static model the effects of an increase in the separation rate on investment in the network and network matching rate mimic the effects induced by a decrease in the arrival rate of offers.

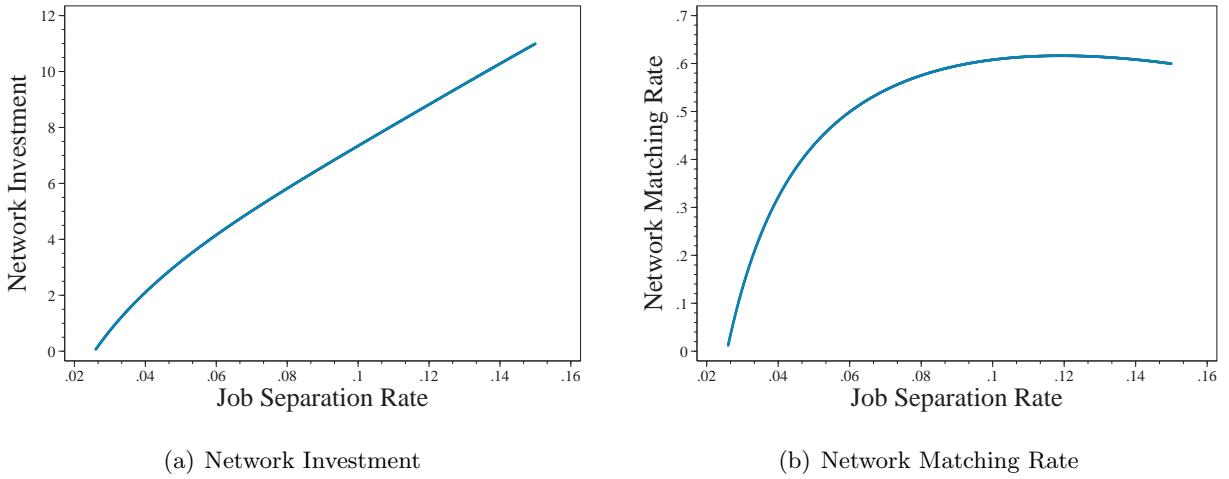


Figure 1: A simulation of the equilibrium for $a = 0.2$, $c = 0.04$ and $\delta \in [0.025, 0.15]$.

investing in connections because the risk of losing a job is low. When the separation rate is high, the value of investing in connections is also low because most of the links will be formed with other job seekers and there will be high competition for needless offers. So, the use of the network will be more pronounced in labor markets where the job separation rate is moderate. In these cases, agents value connections because the risk of losing a job is tangible and they anticipate that competition for referrals is not too severe.

The non-monotonic relationship between network investment and separation rate leads to a similar relationship between network matching rate and separation rate. When the separation rate is low, job contact networks are not highly connected, which implies that the network matching rate is low. In this case, an increase in the separation rate increases the connectivity of the network and, consequently, the probability of finding a job via the network also increases. However, as the separation rate increases further, the network becomes crowded with job seekers. This creates a congestion effect, which eventually reduces the network matching rate. Figure 1 summarizes the comparative statics of the network investment, and of the network matching rate, with respect to the separation rate. In the figure, we have fixed the vacancy rate to $a = 0.2$ and the cost of network investment to $c = 0.04$. For different values of separation rate $\delta \in [0.025, 0.15]$, we have derived the equilibrium level of network investment and the resulting network matching rate.

The positive correlation between network matching rate and separation rate is in sharp contrast from the correlation that is obtained in a model where the network is taken as exogenous (see Proposition 1). As we shall see, the introduction of endogenous effort in searching for jobs via the social network allows to rationalize the empirical patterns that we will document below for the UK labor market.¹³

We conclude the analysis of endogenous job contact networks with a study of their welfare properties. In particular, we consider the problem of a social planner who chooses a symmetric profile $s \in [0, \infty)$ to maximize the expected utility of a randomly selected worker. The objective function of the social planner is:

$$SW(s) = 1 - \delta(1 - a)[1 - \Psi(s)] - cs.$$

We note that increasing network investment has two effects on the employment rate of a worker. On the one hand, it increases the expected number of links of a worker which, in turn, increases his chances of employment. On the other hand, it increases the average connectivity of each of the worker's neighbors and this decreases his hazard rate. While the social planner balances these two effects, individual workers only take into account the first effect. Since workers do not internalize the negative externalities that their links produce on others, the job contact network in the interior equilibrium is over connected relative to what is socially desirable. The following proposition formalizes

¹³The equilibrium expression of network matching rate depends on the assumption we make about what offer a job seeker accepts when he receives both an offer from one of his job contact and a direct offer. In particular, the analysis assumes that he will take the latter. More generally, one might assume that a job seeker will take a direct offer with probability ρ , while with the complementary probability $1 - \rho$ the job seeker takes the offer he accesses from his acquaintances. In this more general specification, the probability that a job seeker finds a job through one of his job contacts is simply $\Psi(s^*)(1 - \rho)$. Furthermore, the probability that a job seeker finds a job through the network conditional on not finding a job through other channels is $\Psi(s^*)[1 - a\rho]/\{1 - a[1 - \Psi(s^*)] - a\rho\Psi(s^*)\}$. For whatever $\rho \in [0, 1]$, the model generates the predictions that the probability of finding a job through the network, both unconditional and conditional on not finding a job through other channels, is inverted U-shaped with respect to the job separation rate.

these intuitions.

Proposition 4 Consider a large labor market and let \tilde{s} be the solution of the planner problem. If $c \geq a\delta(1-a)(1-b)$, then $\tilde{s} = 0$. Otherwise, $\tilde{s} < s^*$ and it is the unique solution to

$$(7) \quad a\delta(1-a)(1-\delta)e^{-\tilde{s}\delta}[1 - \Psi(\tilde{s})] = c.$$

3.3. Robustness: A Dynamic Model

We now couple our basic static network formation model with a dynamic labor market. Workers choose their socialization effort at time zero, anticipating the steady state ensuing in the labor market dynamics. We model the dynamic labor market following the standard random matching approach as in Pissarides (2000), with the only difference that in our environment the matching function takes a specific form that incorporates the network matching rate. Our assumption that investments in the network occur at the beginning of the process formalizes the idea that creating and changing one's social network takes time.

Dynamic Labor Market. We briefly describe our dynamic model of the labor market. There are many firms and many workers, and so each market participant is an atomistic competitor. Time is continuous and $r \in (0, 1)$ is a common discount rate. At each point in time, each unemployed worker receives an instantaneous value of leisure $z > 0$. Firms entering the market open a vacancy at a cost $0 < k < 1$; filled vacancies produce a unit of the unique good of this economy and pay a wage w , which is exogenous.¹⁴ Employed workers lose their job at a rate δ . Unemployed workers find jobs directly by receiving offers at a rate a , which denotes the vacancy rate. Unemployed workers may obtain information about vacant jobs also from their acquaintances who have a needless offer. At each point in time, there is a measure $(1 - u)a$ of workers with a needless offer, where u is the

¹⁴Analogously we can think that the wage is determined by a bargaining model with inside options (which are common knowledge), see, for example, Muthoo (1999). For example, suppose the wage is negotiated every period where, in each period, the worker (respectively the firm) makes a take-it-or-leave-it offer with probability β (respectively $1 - \beta$). If the firm (respectively the worker) rejects the offer, there is a one period holdout where the worker enjoys home productivity γ while the firm enjoys zero profit. The equilibrium (average) wage per period is simply $\beta + (1 - \beta)\gamma$.

unemployment rate. Under a symmetric socialization effort profile, the network matching rate is:

$$(8) \quad \Psi(s, u, a) = 1 - e^{-\frac{a(1-u)}{u}(1-e^{-su})},$$

and the aggregate matching rate is $m(s, u, a) = a + (1 - a)\Psi(s, u, a)$.

Given a symmetric profile of socialization effort s and job separation rate δ , in equilibrium firms and workers maximize their objective function subject to steady state unemployment. We now derive the equilibrium conditions and the steady state condition for arbitrary s .¹⁵

The in-flow into unemployment is simply $\delta(1 - u)$ while the out-flow from unemployment is $um(s, a, u)$. In steady state we must then have that $\delta(1 - u) = um(s, u, a)$, or, equivalently:

$$(9) \quad m(s, u, a) = \frac{\delta(1 - u)}{u}.$$

Let V and J be the present discounted value of expected profits from a vacant job and a filled job, respectively. They must satisfy $rV = -k + m_f(s, u, a)(J - V)$ and $rJ = 1 - w - \delta(J - V)$, where $m_f(s, u, a) = m(s, u, a)u/a$ is the rate at which vacant jobs are occupied. In equilibrium, free entry of firms implies that $V = 0$, or equivalently $m(s, u, a)u/a = k(r+\delta)/(1-w)$. In steady state, vacancy creation is then governed by

$$(10) \quad a = \frac{\delta(1 - u)}{k(r + \delta)}(1 - w).$$

Equilibrium socialization effort. At time zero, workers simultaneously choose a socialization effort anticipating the ensuing equilibrium, i.e., (u, a) solve the system of equations (9) and (10). In particular, given that all other workers choose effort s , worker i chooses socialization effort s_i in order to maximize $U_i - cs_i$, where U_i is the present discounted value of the expected income stream of unemployed worker i . Let W_i be the present discounted value for worker i to be employed, then

¹⁵Since this is standard, we omit several steps in the derivation of these conditions, see Pissarides (2000) for additional details.

$rU_i = z + m_i(s_i, s, u, a)(W_i - U_i)$ and $rW_i = w - \delta(W_i - U_i)$, where

$$m_i(s_i, s, u, a) = a + (1 - a)\Psi_i(s_i, s, a, u) \text{ and } \Psi_i(s_i, s, a, u) = 1 - e^{-\frac{a(1-u)}{us}s_i(1-e^{-su})}.$$

In an interior symmetric equilibrium, $s_i = s > 0$ such that

$$\frac{dm_i(s, s, u, a)}{ds_i} = \frac{rc}{W - U} \frac{r + \delta + m(s, u, a)}{r + \delta},$$

which, after some algebra, can be rewritten as:

$$(11) \quad [1 - \Psi(s, u, a)] \frac{a(1 - a)(1 - u)}{u} \frac{1 - e^{-su}}{s} = \frac{cr[r + \delta + m(s, a, u)]^2}{(r + \delta)(w - z)}.$$

To summarize, an interior symmetric equilibrium is given by (s, u, a) which solves the steady state equation (9), the condition of free entry of firms (10), and the first order condition defining the optimal socialization effort (11).¹⁶

We have not been able to determine analytically the uniqueness of an interior equilibrium and its comparative statics. In what follows, we provide a numerical exercise which shows that, for realistic values of the parameters, there is a unique interior equilibrium and its comparative statics, with respect to job separation rate, is in line with the predictions we derived in our static model.

We choose an interest rate $r = 0.012$, unemployment benefits $z = 0.4$ and wage $w = 0.8$. We also fix the values of the cost of socialization to $c = 0.6$ and the cost of opening a vacancy $k = 0.8$. We then find the steady state equilibrium for different values of the job separation rate δ between 0.5 percent and 10 percent, and we calculate equilibrium network investment, network matching rate, unemployment rate and vacancy rate. The range of job destruction rate that we consider is in line with our findings for the UK labor market, which we discuss in the next section. For intermediate values of the job separation rate in this range, we find a steady state unemployment around 8 percent and an average network matching rate around 30 percent; these are also in line with the UK data.

¹⁶As in the static model, there always exists an equilibrium where no worker socializes, i.e., $s_i = 0$ for all $i \in N$. In this equilibrium, the network matching rate is zero and (a, u) satisfy conditions (9) and (10).

Figure 2 summarizes this exercise.¹⁷

4. Information transmitted in the network and labor market conditions: UK empirical patterns

We investigate the correlation between labor market conditions, the extent that workers use their network of contacts in job search, and the rate at which workers find jobs via their network of contacts. We use the UK Quarterly Labour Force Survey (QLFS), which allows us to explore the relationship between the job separation rate, our proxy of the labor market conditions, and both the probability of finding a job via social networks and the use of networks in job search.

Each wave of the QLFS covers a representative sample of the UK population that includes around 60,000 households incorporating from 125,000 to 150,000 individuals, depending on the wave. We use data from the first quarter of 1995 to the fourth quarter of 2004. Only males of working age (aged 16 to 64) are considered, so that we are left with an average of 43,000 individuals per wave. We divided our sample into 20 regions, which are defined in the survey design using the information about the respondents' usual residence.¹⁸ We construct all our variables at the regional level. In our estimation, we focus on job seekers because we think that, since they are actively looking for a job, they could be using their social network strategically. Job seekers are respondents who reported that they were actively looking for a job. In some regressions, we consider an alternative sample composed of workers who were unemployed at the time they were looking for a job, and then found a job; for these workers we can directly map their search strategies into how successful these strategies were.

¹⁷We have conducted a similar numerical exercise for different values of parameters to control the robustness of these results. The analysis is available upon request to the authors.

¹⁸This is the finer level of residence information available in the QLS until 2001. The regions are: Tyne & Wear; rest of Northern region; South Yorkshire; West Yorkshire; rest of Yorkshire & Humberside; East Midlands; East Anglia; inner London; outer London; rest of South East; South West; West Midlands (Met county); rest of West Midlands; greater Manchester; Merseyside; rest of North West; Wales; Strathclyde; rest of Scotland; Northern Ireland.

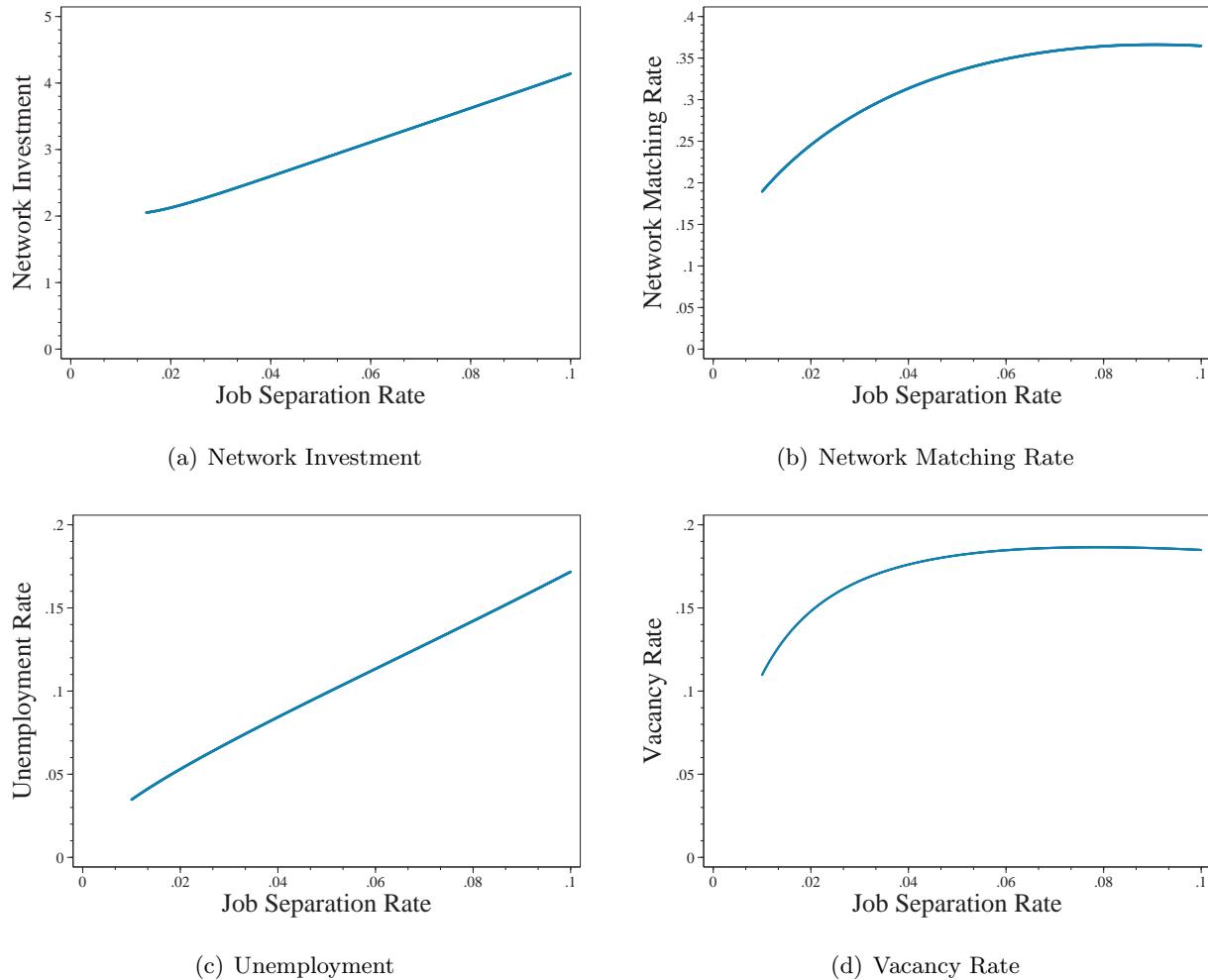


Figure 2: The steady state equilibrium of the dynamic model for $r = 0.012$, $z = 0.4$, $c = 0.6$ and $k = 0.8$ and $\delta \in [0.005, 0.10]$.

In each quarter, job seekers were asked about their main job search method. Respondents were given a list of available options, from which they could choose only one of them. The available options were: visit a jobcentre/jobmarket or training and employment agency office; visit a careers office; visit a jobclub; have your name on the books of a private employment agency; advertise for jobs in newspapers or journals; answer advertisements in newspapers and journals; study situations vacant in newspapers or journals; apply directly to employers; ask friends, relatives, colleagues or trade unions about jobs; wait for the results of an application for a job; do anything else to find work. We are interested in the proportion of job seekers in a given region that use friends, relatives and colleagues as a main job search method in each period. This variable is a measure of the extent that workers use their networks of contacts, and it constitutes our proxy for *network investment* in job search.¹⁹

In addition, workers who found a job in the previous quarter were asked how they found it. Again, respondents were given a list of available options, from which they could choose only one of them. In particular, the available options were: replying to a job advertisement; job center; careers office; job club; private employment agency or business; direct application; hearing from someone who worked there; some other way.²⁰ We are interested in the proportion of workers that, in each region, reported to have found his new job by “hearing from someone who worked there” in each period. This variable proxies the *network matching rate*.

While the literature typically concentrates on the effect of network size or population density on the probability of finding a job through the network,²¹ we are interested in the effect of labor

¹⁹The survey nests search via friends and colleagues with search via trade unions, which is not ideal for our proxy. Since the proportion of unionized workers has steadily declined in the UK in our sample period, in our analysis we will control for this by introducing time dummies.

²⁰There have been some changes in this question throughout the history of the QLFS. Since the second quarter of 2005, this question is addressed to everybody who found a new job in the last twelve months or less. Furthermore, some answers of the second quarter of 1994 are clearly miscoded—a change of the coding was introduced at that time. For these reasons, we excluded all waves before 1994:Q3 and after 2005:Q1 from our sample.

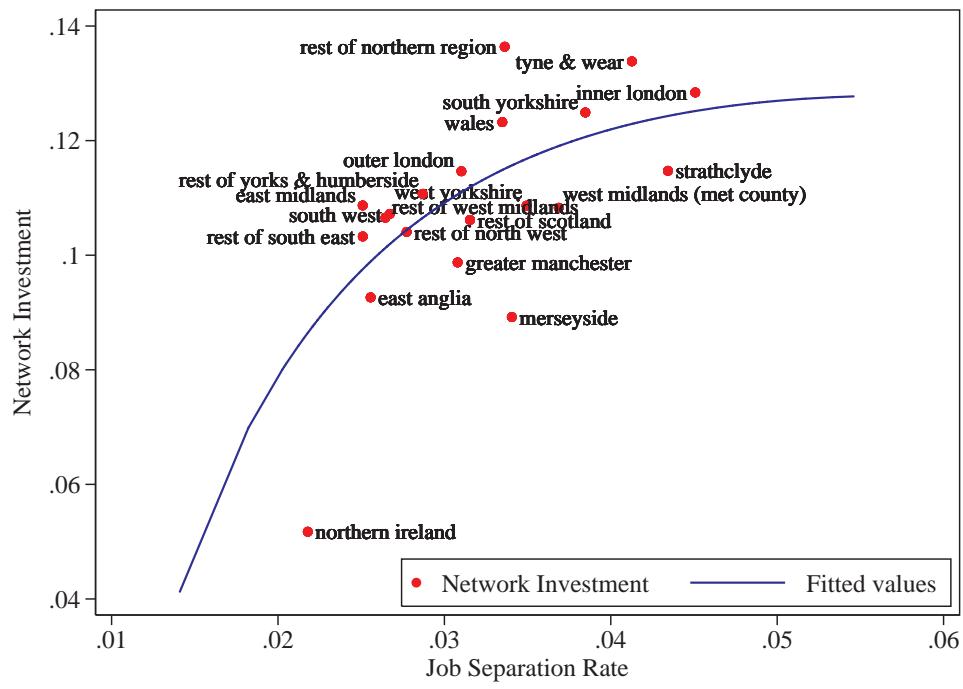
²¹See Beaman (2012) and Wabha and Zenou (2005): both find evidence of congestion when network size increases; in our model, we derive the equilibrium conditions when population size goes to infinity, but as n increases the effect

market conditions. So, instead of using the number of workers in the market, we use a measure of the riskiness to become unemployed in a given quarter, namely the *job separation rate*, which we calculate at a regional level. We have constructed the unemployment rate in each region using the ILO definition: the proportion of unemployed workers looking for a job or waiting to start a job in the next two weeks over the whole active population. We obtained an average yearly unemployment rate over the period of 7.75 percent, ranging from a minimum of 3.19 percent to a maximum of 19.53 percent. Then, we have calculated the job separation rate (i.e., the probability of transition from employment to unemployment) using the flows of workers into and out of unemployment at regional level using quarterly data, which is the highest frequency available in the QLFS. In order to reduce time aggregation biases, we calculated the separation rate according to equation (5) of Shimer (2012), which is meant to take into account the problem that, while data is available only at discrete date, the underlying environment keeps changing over time. Taking yearly averages, we obtained an average job separation rate over the period of 3.21 percent, which is consistent with earlier work, ranging from a minimum of 1.41 percent to a maximum of 5.46 percent.

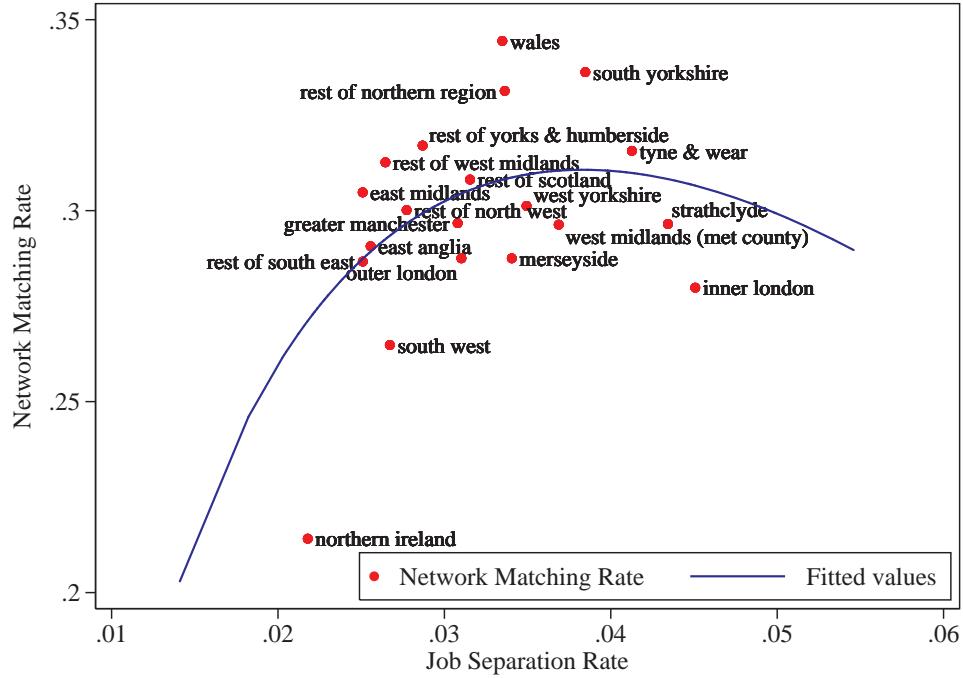
We are interested in studying how network investment and network matching rate change when the job separation rate changes. In line with our theoretical predictions, plotting the averages in each region during the whole time period, a positive and concave relationship emerges using a polynomial fit, as depicted in the two panels of Figure 3.

To investigate the regional differences in the use and effectiveness of social networks in job search, we calculate our proxy of network investment and network matching rate at a yearly frequency, since we want to focus on medium and long run changes in the use of social networks. As for the variables capturing labor market conditions, we take year averages for the 20 regions from 1995 to 2004, so we end up with 200 observations. We remark that the results we shall provide are robust to longer time spans of aggregation of the data, for example, five-year averages (see Appendix A.3). In this sample, the proportion of workers that looked for a job via social networks is 10.88 percent on average, ranging from 3 percent to 19.08 percent, and the proportion of workers that found a job

is in line with other studies, i.e., there is a congestion effect if the cost of socialization is sufficiently small.



(a) Network Investment and Job Separation Rate, Regional Averages



(b) Network Matching Rate and Job Separation Rate, Regional Averages

Figure 3: Regional averages in the whole time period 1995–2004 of our proxies for network investment and network matching rate plotted against the job separation rate.

via friends or relatives working in the same firm has an average value of 29.78 percent, ranging from 15.69 percent to 43.17 percent.

We take two approaches to more formally investigate the data. We first understand how much of the variation of unemployment, job separation rate, network investment and network matching rate are due to regional variations, rather than time variation. We then try to capture how much of the regional variation in network investment and network matching rate can be explained by local labor market conditions, captured by the job separation rate.

The first model that we analyze is a simple linear probability regression where the independent variables are year and regional dummies. That is:

$$Y_{j,t} = \alpha_0 + \sum_{j=1,19} \alpha_j I_j + \sum_{t=1,10} \beta_t I_t + \epsilon_t,$$

where $Y_{j,t}$ is the value of the dependent variable in a given region in a given period (unemployment rate, job separation rate, network investment and network matching rate), I_j is an indicator function that takes value 1 if the observation comes from region j , and I_t is an indicator function that takes value 1 in year t .

The results, reported in Table 1, show that most of the variation of unemployment, job separation rate, network investment and network matching rate is explained by regional differences. Regional and year dummies explain 91.4 percent of the variation in unemployment, and regional dummies explain nearly two thirds of this for unemployment. The regional variation is even more pronounced for the job separation rate: 65.8 percent of the variation comes from regional differences, whereas variation over time explains less than 5 percent. Regional and year dummies explain 64.8 percent of the variation of network investment rate; regional dummies alone explain 60 percent of such variation. Similarly, regional and year dummies explain 47.5 percent of the variation in the network matching rate, with regional differences explaining more than 80 percent of this variation.

We then analyze a linear probability model where we regress network investment and network

Table 1: Linear probability model with only regional and time dummies by region of residence.

	Unemployment Rate		Separation Rate		Network Investment		Network Matching Rate	
Regional Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	No	Yes	No	Yes	No	Yes	No
R^2	0.914	0.557	0.704	0.658	0.648	0.390	0.475	0.393
Adj. R^2	0.899	0.510	0.656	0.622	0.590	0.325	0.389	0.328
Obs.	200	200	200	200	200	200	200	200

Source: UK QLFS, male respondents, aged 16-64, waves from 1995 to 2004.

Standard errors bootstrapped using 1000 repetitions, in parenthesis. *** $p < .01$, ** $p < .05$, * $p < .1$.

matching rate against the job separation rate and its squared value. Formally, the model is:

$$Y_{j,t} = \gamma_0 + \gamma_1 \delta_{j,t} + \gamma_2 \delta_{j,t}^2 + \epsilon_{j,t},$$

where $Y_{j,t}$ is the value of the dependent variable in a given region in a given period (in this case, network investment and network matching rate) and $\delta_{j,t}$ is the job separation rate in region j at time t . In some regression, we also include time dummies to fully control for time trends.

Table 2 reports the results for network investment and for network matching rate. We find that the separation rate has a significant and, on average, positive effect on network investment, and that the coefficient of its squared value is significant and negative. In line with our theoretical model, worse labor market conditions give incentives to workers to rely more on their social networks, but this effect is lower the higher the job separation rate. While the overall impact is, on average, positive in the range of values that the independent variables take, confirming a positive correlation between network investment and the riskiness of the labor market, when the separation rate is more than 4.7 percent the effect starts to decrease. Hence, an increase in the separation rate eventually decreases network investment in regions that face extremely bad labor market conditions.

To have a quantitative idea of the magnitude of these effects, a back-of-the-envelope calculation suggests that an increase of one percentage point of the job separation rate around its average value is associated to an increase in network usage of 1.24 percentage points. These calculations are not different when we consider job seekers who are not employed.

The estimates in Table 2 also show that there is an increasing and concave relationship between network matching rate and job separation rate. Around the average value of the job separation rate, an increase of one percentage point of the job separation rate is associated to an increase in network matching rate of 0.58 percentage points. While the relationship between network matching rate and job separation rate is on average positive in our sample, it becomes negative for separation rates above 3.92 percent.

The effects reported in Table 2 are robust to the introduction of year dummies, which allows to control for time aggregation (see footnote 19). Qualitatively similar results are obtained by removing one of the regions at a time, so that we can confidently conclude that our estimates do not depend on few outliers.

So far, we have used the job separation rate computed at a regional level. This may be problematic since labor market conditions influence differently workers that have different employment opportunities. We tackle this issue by computing the separation rate separately for workers of different educational achievement in each period and in each region. In other words, we are changing the definition of labor market: instead of referring to local labor markets, we are considering that only workers with similar educational attainments are in the same local labor market.

We divide our sample into low, medium and high skilled workers. We use the definition of skill levels of individuals put forward by the International Standard Classification of Education (ISCED1997). This classification is as follows: Low = ISCED 0–2 (pre-primary education; primary or first stage of education of basic education; lower secondary education or second stage of basic education); Middle = ISCED 3–4 ([upper] secondary education; post-secondary non tertiary education); High = 5–6 (first stage of tertiary education [not leading directly to an advanced research qualification]; second stage of tertiary education [leading to an advanced research qualification]).²²

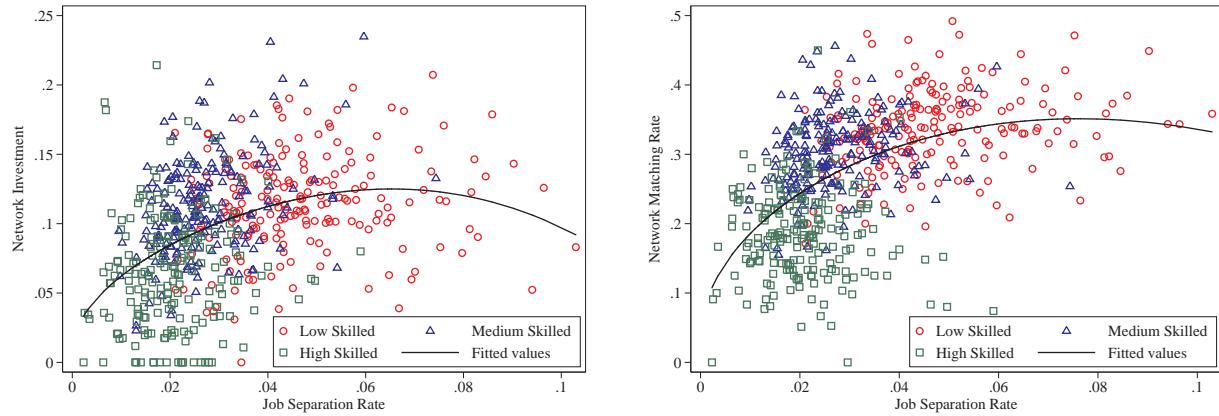
²²When no information was available on the degree obtained, i.e. for all respondents that got a degree abroad, we

Table 2: Linear probability model regressing the proportion of job seekers using friends and relatives as the main job search method and the proportion of workers that found a job via their social network against the job separation rate by region of residence.

	Network Investment			Network Matching Rate		
	Job Seekers	Unemployed	Job Seekers	Job Seekers	Unemployed	Job Seekers
δ_t	5.845*** (1.665)	5.553*** (1.535)	5.572*** (1.702)	5.245*** (1.560)	10.593*** (2.497)	10.723*** (2.549)
δ_t^2	-62.120*** (24.089)	-59.249*** (21.472)	-58.826*** (24.341)	-55.361*** (21.725)	-134.964*** (34.939)	-138.488*** (35.041)
Year Dummies	No	Yes	No	Yes	No	Yes
R^2	0.201	0.429	0.180	0.398	0.106	0.179
Adj. R^2	0.193	0.396	0.172	0.362	0.097	0.131
Obs.	200	200	200	200	200	200

Source: UK QLFS from 1995 to 2004, male respondents, aged 16-64.

Standard errors bootstrapped using 1000 repetitions, in parenthesis. *** $p < .01$, ** $p < .05$, * $p < .1$.



(a) Network Investment and Job Separation Rate, Regional Averages by Skill Level (b) Network Matching Rate and Job Separation Rate, Regional Averages by Skill Level

Figure 4: Regional averages by skill level in the whole time period 1995–2004 of our proxies for network investment and network matching rate plotted against the job separation rate.

Using this definition of the labor market, we obtained an average job separation rate of 3.17 percent, ranging from a minimum of 0.23 percent to a maximum of 10.3 percent. The job separation rate is very different across skill groups. It is only 2.08 percent on average for high skilled workers, it is 2.69 percent for medium skilled workers, and it reaches an average value of 4.74 percent for low skilled workers. The relationship between the job separation rate and network investment, and network matching rate, is depicted in the two panels of Figure 4. A polynomial fit of the data suggests a positive and concave relationship of our proxies of network investment and network matching rate with the job separation rate, as predicted by our model. Furthermore, Figure 4 suggests that differences across skill groups account for most of the variation in network investment and network matching rate, relative to differences within skill groups or through time.²³

The results of the regressions for our proxies of network investment and network matching rate

use “age left full-time education”, and classified them as low skill if they left education before age 16, high skilled if they left education after age 21 and medium skilled otherwise. See Manacorda, et al. (2006) for a discussion of this point.

²³Simple regressions using time and educational dummies (available upon request) confirm this.

are reported in Table 3.²⁴ The estimation results are qualitatively similar to the ones where workers with different skills were pulled together within a region (Table 2). For example, an increase of one percentage point of the separation rate is associated to an increase in the odds ratio of looking for a job through the social network by 1.13 percentage points and of finding a job through the social network by 2.91 percentage points.

Quantitatively, the relationship between job separation rate and network matching rate is very different across workers with different skills. For low skilled workers, who experience a job separation rate higher than the average, an increase in job separation rate of one percentage point around their average is associated to a small increase of 0.46 percent in network investment, and of a 1.57 percent in network matching rate. Furthermore, the predicted effect on the network matching rate is negative for 12.5 percent of the observations of low skilled workers. In contrast, the effect of a one percentage increase in the job separation rate from its average value for highly skilled workers would imply a predicted increase in network investment of 1.60 percent, an increase in the network matching rate of 3.84 percent, and the predicted effect on the network matching rate is positive for all the observations of high skilled workers. These findings are in line with our model, which predicts that adverse labor market conditions should affect more workers who rely on job contact networks more than the average, which as can be seen in panel (a) of Figure 4, are low skilled workers.²⁵

Contrary to the prediction of a model with exogenous job contact networks, the stylized fact emerging from this section is that the separation rate is associated positively with network investment, and network matching rate, when the job separation rate is low and negatively when it is high. Furthermore, a worsening of labor market conditions may reduce the effectiveness of networks in

²⁴In Appendix A.3, we provide the estimates when we perform the exercise separately for the three skill groups of workers (see Tables 6 and 7). The results show that the positive and concave relationship between separation rate and network investment, and network matching rate, is also present when we exploit variation across regions within workers with the same educational attainment. We do not find qualitative differences on the way network investment and network matching rate are affected by job destruction rate across skill groups.

²⁵Furthermore, as documented by Battu, et al. (2011), Holzer (1987) and Elliott (1999), minority workers are often low skilled and tend to rely more on informal job search channels.

Table 3: Linear probability model regressing the proportion of job seekers using friends and relatives as the main job search method and the proportion of workers that found a job via their social network against the job separation rate by skill level and region of residence.

	Network Investment		Network Matching Rate		
	Job Seekers	Unemployed Job Seekers	Job Seekers	Unemployed	Job Seekers
δ_t	2.710*** (0.344)	2.515*** (0.342)	2.550*** (0.363)	2.336*** (0.374)	6.043*** (0.581)
δ_t^2	-21.477*** (3.889)	-18.751*** (3.713)	-20.333*** (3.927)	-17.328*** (3.949)	-42.668*** (6.439)
Year Dummies	No	Yes	No	Yes	No
R^2	0.159	0.224	0.127	0.192	0.260
Adj. R^2	0.156	0.210	0.125	0.177	0.257
Obs.	600	600	600	600	600

Source: UK QLFS from 1995 to 2004, male respondents, aged 16-64.

Standard errors bootstrapped using 1000 repetitions, in parenthesis. *** $p < .01$, ** $p < .05$, * $p < .1$.

a job search for low skilled workers, who are the ones relying more on networks in the first place. In this sense, low skilled workers become even more vulnerable in downturns. The overall message is that the use of networks, and their efficiency in matching workers to jobs, depends on the labor market conditions. This should be taken into account when designing labor market policies aimed at reducing unemployment, because these effects are different across groups of workers and they might affect search behavior in a way that partially offsets their impact.

5. Conclusion

In this paper, we investigate how labor market conditions affect the formation of job contact networks and how this interplay shapes labor market outcomes. We have shown that, taking into account the endogeneity of job contact networks leads to predictions that are in line with the documented empirical patterns.

Our empirical analysis has focused on regional differences. This is in line with the underlying premise of our theoretical model, which assumes that creating and changing networks takes more time than other labor market variables to adjust (such as vacancy rate and wage). Despite our model taking this assumption to the extreme (for example, network investment is once and for all), similar results could be obtained in a model where network investment can be adjusted over time, but at a lower rate than other labor market variables. This implies that one should also observe similar correlations by exploiting time variations. In a previous version of the paper (Galeotti and Merlino, 2010) we have explored how the individual probability of finding a job via the network was affected by labor market conditions taking advantage of the panel dimension of the UK QLFS. There, we also found qualitatively similar results at the individual level using fixed effects logit models with individual and time fixed effects.

In the model, we assume symmetry across all workers when they decide how much to invest in searching for jobs via the network. In particular, all workers earn the same wage, and the reason to invest in connections comes from the risk of becoming unemployed. If wages were dispersed then there would be an additional reason to invest in connections, which is to find a job that pays a higher wage.

Furthermore, workers earning a different wage to start with will have different incentives to search. In particular, workers earning a higher wage will find it less profitable to invest in the network because the probability that their acquaintances will pass information about vacancies that pay high salaries will be lower (as they might want to keep that job for themselves). Despite these complications, for each particular worker, it will still be the case that an increase in the job separation rate has two opposite implications. On the one hand, it increases the incentives to invest in connections because it is more likely that the worker has to actively search for better jobs. On the other hand, it decreases the incentives to invest in connections because each contacted worker will either have less incentives to spread the information or more contacts to refer the vacancy to. This is the basic trade-off that generates all the main insights in our simple model with symmetric workers. We expect that this trade-off plays a similar role once different forms of heterogeneity are introduced in the model. A full-fledged analysis is left for further research.

We have focused on labor markets but the question of how the state of the economy shapes informal institutions is much broader. For example, there is a large amount of empirical work on the effects of social capital on economic growth. Often this work struggles with the fact that social capital is an endogenous variable, raising concerns of identification of the models. Referring to this literature, Durlauf (2002, pp. F474) noted: "...it seems clear that researchers need to provide explicit models of the co-determination of individual outcomes and social capital, so that the identification problems (...) may be rigorously assessed". Our paper aims to contribute to this line of research by providing a tractable model, where the interplay amongst aggregate variables and individual investment in informal organizations is mapped into equilibrium correlations amongst these variables, that cannot be accounted for in a model where informal institutions are exogenous.

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Appendix

A.1. Proofs of Lemmas and Propositions

Proof of Proposition 1 First, it is straightforward to verify that $\frac{\partial \Psi}{\partial s}(s) > 0$ and that $\frac{\partial \Psi}{\partial a}(s) > 0$. We now show that $\Psi(s)$ is decreasing in δ . The derivative of $\Psi(s)$ with respect to δ has the same sign as the derivative of $\frac{(1-\delta)}{\delta} (1 - e^{-s\delta})$ with respect to δ , which is given by

$$(12) \quad \frac{e^{-s\delta}[\delta(1-\delta)s+1]-1}{\delta^2}.$$

Expression (12) is negative when $e^{-s\delta}[\delta(1-\delta)s+1] < 1$ which is equivalent to $-s\delta + \ln(1+\delta(1-\delta)s) < 0$. This holds because $-s\delta + \ln(1+\delta(1-\delta)s)|_{s=0} = 0$ and $-s\delta + \ln(1+\delta(1-\delta)s)$ is decreasing in s . Hence, $\frac{\partial \Psi}{\partial \delta}(s) < 0$ for all $s > 0$. Second, the comparative statics with respect to the matching rate and the unemployment rate follows by the comparative statics of the network matching rate. This concludes the proof of Proposition 1. \blacksquare

Proof of Proposition 2 Suppose an interior equilibrium exists. Consider a profile \mathbf{s} where $s_j = s$, $\forall j \neq i$. Under profile \mathbf{s} , the probability that $i \in \mathcal{B}$ does not receive an offer from the network is

$$\phi_i(s_i, s) = \left[1 - p_i \frac{1 - (1-p)^{n\delta}}{\delta np} \right]^{na(1-\delta)},$$

where $p_i = s_i s / [s_i + (n-1)s]$ and $p = s^2 / [s_i + (n-1)s]$. Next note that for every $s > 0$, i 's best response, say \hat{s}_i , has the property that $\hat{s}_i s \leq [\hat{s}_i + (n-1)s]$. Indeed, if $\hat{s}_i s > [\hat{s}_i + (n-1)s]$, then i could decrease his own networking effort and still be linked to any arbitrary worker with probability 1. Hence, an interior equilibrium s^* solves:

$$\frac{\partial EU_i}{\partial s_i}(s^*, s^*) = -\delta(1-a) \frac{\partial \phi_i}{\partial s_i}(s^*, s^*) - c = 0.$$

Since

$$\begin{aligned} \frac{\partial \phi_i}{\partial s_i}(s_i, s) &= a(1-\delta)n \left(1 - \frac{s_i}{\delta ns} \left(1 - \left(1 - \frac{s^2}{s_i + (n-1)s} \right)^{\delta n} \right) \right)^{a(1-\delta)n-1} \\ &\quad \left(\frac{s_i s}{(s_i + (n-1)s)^2} \left(1 - \frac{s^2}{s_i + (n-1)s} \right)^{\delta n-1} - \frac{1}{\delta ns} \left(1 - \left(1 - \frac{s^2}{s_i + (n-1)s} \right)^{\delta n} \right) \right), \end{aligned}$$

in large labor markets, we have that:

$$\lim_{n \rightarrow \infty} \frac{\partial \phi_i}{\partial s_i}(s_i, s) = -\frac{a(1-\delta)}{s\delta} \left(1 - e^{-s\delta} \right) e^{-\frac{a(1-\delta)}{\delta} \frac{1-e^{-s\delta}}{s} s_i}.$$

Therefore, s^* must solve

$$(13) \quad \frac{a(1-a)(1-\delta)}{s^*} \left(1 - e^{-s^*\delta} \right) e^{-\frac{a(1-\delta)}{\delta} \left(1 - e^{-s^*\delta} \right)} = c,$$

which is equivalent to condition (6) stated in Proposition 2. It is easy to see that $\frac{\partial \phi_i}{\partial s_i}(s_i, s)$ is continuous in the limit as it converges to (13) when n goes to infinity,²⁶ which ensures that the solution of the n -game converges to the solution of the limit game. We now show that there exists a unique solution to this equation and we derive the conditions for existence. We start noticing that the LHS is decreasing in s^* because both $(1 - e^{-s^*\delta}) / s^*$ and $e^{-\frac{a(1-\delta)}{\delta} \left(1 - e^{-s^*\delta} \right)}$ are decreasing in s^* . Furthermore, when s^* goes to 0, the LHS converges to $a\delta(1-a)(1-\delta)$, while when s^* goes to infinity the LHS converges to 0. Since marginal returns are continuous in s_i , it follows that an interior symmetric equilibrium exists if and only if $c < a\delta(1-a)(1-\delta)$, in which case there is only one symmetric interior equilibrium. This concludes the proof of Proposition 2. ■

Proof of Proposition 3 We first prove part 1. We derive $ds^*/d\delta$ by implicit differentiation of (6) and obtain

$$(14) \quad \frac{ds^*}{d\delta} = \frac{e^{-s^*\delta} [s(1-\delta) + 1] - 1 + a(1-\delta)(1 - e^{-s^*\delta}) \frac{1 - e^{-s^*\delta} - \delta(1-\delta)s e^{-s^*\delta}}{\delta^2}}{(1-\delta) \left(\frac{1 - e^{-s^*\delta} - s^* \delta e^{-s^*\delta}}{s^*} + a(1-\delta)(1 - e^{-s^*\delta}) e^{-s^*\delta} \right)}.$$

²⁶In other words, it is possible to show that for each $\epsilon > 0$, there exists an $n(\epsilon)$ such that for each $n > n(\epsilon)$, the distance of the two expressions is at most ϵ .

Since the denominator is positive, the sign of this derivative depends on the sign of the numerator. Defining $x = \frac{a(1-\delta)(1-e^{-s^*\delta})}{\delta}$, we rewrite expression (14) as follows

$$(15) \quad \frac{ds^*}{d\delta} = \frac{\frac{dx}{d\delta} + (1-x)\frac{dx}{d\delta} - \delta \left(\frac{dx}{d\delta}\right)^2 + \delta(1-x)\frac{d^2x}{d^2\delta}}{a \left[\frac{1-e^{-s^*\delta}-\delta s^* e^{-s^*\delta}}{s^*} + (1-e^{-s^*\delta}) a(1-\delta) e^{-s^*\delta} \right]},$$

where

$$\frac{dx}{d\delta} = a \frac{e^{-s^*\delta} [\delta(1-\delta)s^* + 1] - 1}{\delta^2} < 0.$$

The derivative of the numerator of expression (15) with respect to δ when $ds/d\delta = 0$ is

$$(16) \quad \frac{(1-a)}{s^*} e^{-x} \left[\frac{dx}{d\delta} + (1-x)\frac{dx}{d\delta} - \delta \left(\frac{dx}{d\delta}\right)^2 + \delta(1-x)\frac{d^2x}{d^2\delta} \right],$$

where,

$$\frac{d^2x}{d^2\delta} = -\frac{2}{\delta} \frac{dx}{d\delta} - \frac{sae^{-\delta s^*}(2+s-\delta s)}{\delta}.$$

After some algebra, (16) can be written as

$$\frac{(1-a)}{\delta s^*} e^{-x} \left[\frac{dx}{d\delta} \left(x - \delta \frac{dx}{d\delta} \right) - (1-x)sae^{-\delta s^*}(2+s-\delta s) \right].$$

The first term in the square brackets is always negative because $\frac{dx}{d\delta}$ is always negative, and x is positive. On the other hand, $2+s-\delta s > 0$ for $\delta \in [0, 1]$ and $s \geq 0$. Note furthermore that when $\frac{dFOC}{d\delta} = 0$, by (15) it follows that $\frac{dx}{d\delta} = -\frac{x}{\delta(1-x)} < 0$, which implies that $(1-x) > 0$. Hence the last term is also negative. Furthermore, $\frac{dFOC}{d\delta}$ is positive when $\delta = 0$ and negative when $\delta = 1$. Since when $\frac{dFOC}{d\delta} = 0$, $\frac{d^2FOC}{d^2\delta}$ is negative, by continuity, (15) crosses the δ -axis only once, precisely at $\bar{\delta}(a) > 0$. Hence, if $\delta < \bar{\delta}(a)$, the derivative is positive, while if $\delta > \bar{\delta}(a)$, it is negative. Note that this is the value of δ where s^* is maximum. This concludes the first part of the proof of Proposition 3.

We now turn to the second part of Proposition 3. The change in equilibrium network productivity

when δ changes is described by:

$$(17) \quad \frac{d\Psi(s, a, \delta)}{d\delta} = a\phi(s^*) \left[-\frac{1 - e^{s^*\delta}}{\delta^2} + (1 - \delta)e^{-s^*\delta} \left(\frac{s^*}{\delta} + \frac{ds^*}{d\delta} \right) \right].$$

While the first term in the square parenthesis is always negative, the sign of the second one depends on the sign of $ds^*/d\delta$. Using part 1 of Proposition (3), $ds^*/d\delta$ is negative when δ is sufficiently high, and hence $d\Psi(s, a, \delta)/d\delta$ would be negative as well. When δ tends to 0, $ds^*/d\delta$ tends to ∞ . Furthermore, the limit of expression (17) as δ goes to 0 is also ∞ . Since the derivative is continuous, its sign is positive when δ is close enough to 0. This concludes the proof of Proposition 3. ■

Proof of Proposition 4 The derivative of social welfare with respect to socialization effort is:

$$\frac{dSW}{ds}(s) = \delta(1 - a)a(1 - \delta) \left[1 - \frac{1 - (1 - \frac{s}{n})^{n\delta}}{n\delta} \right]^{na(1-\delta)-1} \left(1 - \frac{s}{n} \right)^{n\delta-1} - c,$$

and in large labor markets become

$$\lim_{n \rightarrow \infty} \frac{dSW}{ds}(s) = \delta(1 - a)a(1 - \delta)e^{-s\delta}e^{-\frac{a(1-\delta)}{\delta}(1-e^{-s\delta})} - c.$$

Note that $\frac{dSW}{ds}(0) = a\delta(1-a)(1-\delta)-c$, $\lim_{s \rightarrow \infty} \frac{dSW}{ds}(s) = -c$. Moreover, $\frac{dSW}{ds}(s)$ is strictly decreasing in s , since both $(1 - e^{-s\delta})$ and $s\delta$ are strictly increasing in $s \in (0, \infty)$. Hence, if $c \geq a\delta(1-a)(1-\delta)$, the social planner chooses $\tilde{s} = 0$, while for all $c < a\delta(1-a)(1-\delta)$ the optimal solution \tilde{s} is uniquely defined by

$$a\delta(1 - a)(1 - \delta)e^{-\frac{a(1-\delta)}{\delta}(1-e^{-\tilde{s}\delta})-\tilde{s}\delta} = c.$$

Finally, it is easy to verify that at equilibrium s^* , $\frac{dSW}{ds}(s^*) < 0$, and since $\frac{dSW}{ds}(s)$ is decreasing in s , it follows that $\tilde{s} < s^*$ for all $c < a\delta(1-a)(1-\delta)$. This concludes the proof of Proposition 4. ■

A.2. Indirect information flow

This appendix examines the implications of indirect information flow in the matching process of workers with firms and how it shapes workers' socialization incentives. Information flow in the

network now follows the following process. As in the basic model, each worker l with a needless offer gives it to one of his unemployed neighbors, chosen at random. If worker l has only employed friends, then he chooses one of them at random, say j , and gives him the information. For simplicity, we assume that if j had himself a needless offer, then the offer he receives from l is lost. If, on the contrary, worker j did not have a needless offer, then he selects at random one of his unemployed friends, say i , and passes the information to him. We also assume that the information passed from j to i reaches i with probability $\gamma \in [0, 1]$, where γ is the decay in the information flow. So, information now may flow two-steps away in the network.

We observe that a job seeker does not hear about new jobs from his friends if: 1) he does not access information from his friends who received a needless offer directly and 2) he does not get information from his contacts who are employed, do not have a needless offer directly, but have heard of a job opportunity from at least one of their friends. The probability associated to the event described in 1) is given by (4). We now derive the probability associated to the event described in 2). For concreteness, in what follows, $i \in \mathcal{B}$ and chooses s_i , while all other workers choose effort s . Moreover, worker j is employed and he does not have a needless offer, $j \in \mathcal{N} \setminus (\mathcal{B} \cup \mathcal{O})$, while worker $l \in \mathcal{O}$.

First, suppose j and l are linked, i.e., $g_{jl} = 1$. The probability that j receives information from l is:

$$(1 - p_i)(1 - p)^{n\delta-1} \sum_{v=1}^{n(1-\delta)} \Pr(\eta_l(\mathcal{N} \setminus \{\mathcal{B}\}) = v | g_{lj} = 1) \frac{1}{v}.$$

That is, worker l 's friends must be all employed, $(1 - p_i)(1 - p)^{n\delta-1}$, and, conditioning on having v links, worker l gives the information to j with probability $1/v$. So, if worker j is linked with ω workers such as l , the probability that j does not receive information is:

$$\left[1 - (1 - p_i)(1 - p)^{n\delta-1} \sum_{v=1}^{n(1-\delta)} \Pr(\eta_l(\mathcal{N} \setminus \{\mathcal{B}\}) = v | g_{lj} = 1) \frac{1}{v} \right]^\omega.$$

Summing across all possible number of j 's neighbors who are employed and with a needless offer, we

obtain the probability that j accesses at least an indirect offer:

$$\Theta(\mathbf{s}) = 1 - \sum_{\omega=0}^{|\mathcal{O}|} B(\omega|p, |\mathcal{O}|) \left[1 - (1-p_i)(1-p)^{n\delta-1} \sum_{v=1}^{n(1-\delta)} \Pr(\eta_l(\mathcal{N} \setminus \{\mathcal{B}\}) = v | g_{lj} = 1) \frac{1}{v} \right]^\omega,$$

and in a large labor market it is equal to:

$$(18) \quad \Theta(\mathbf{s}) = 1 - e^{-a(e^{-s\delta} - e^{-s})}.$$

Note that in a complete network worker l has always links with unemployed workers and therefore every worker like j will never receive information. When the network is not complete, it is easy to verify that the probability that j gets information is non-monotonic in s —it first increases when s is low to begin with and then it decreases. Therefore, greater connectivity of workers other than unemployed i may have a positive effect on the probability that i gets a job. This illustrates a novel effect which emerges from indirect information flow. In fact, when the network is not very connected to start with, high socialization investments of other workers have a positive effect on the value of worker i 's socialization investment because it makes more likely that i 's neighbors have job information to pass along.

Second, consider our original job seeker i and suppose he has η links with workers like j above. The probability that i does not receive an offer from each of these η contacts is:

$$\sum_{d=0}^{\eta} B(d|\Theta(\mathbf{s}), \eta) \left[1 - \sum_{t=1}^{n\delta} \Pr(\eta_j(\mathcal{B}) = t | g_{ij} = 1) \frac{\gamma}{t} \right]^d.$$

In words, with probability $B(d|\Theta(\mathbf{s}), \eta)$, d out of the η contacts of i have received an offer from one of their employed friends. Suppose j is one of these individuals; then the probability that i receives information from j depends on the level of the decay in the information flow and the number of unemployed workers connected to j . Summing across all possible number of links that worker i can

have with workers like j , we obtain the probability that i does not access an indirect offer:

$$\phi_i^{in}(s_i, \mathbf{s}_{-i}) = \sum_{\eta=0}^{n(1-a)(1-\delta)} B(\eta|p_i, n(1-a)(1-\delta)) \sum_{d=0}^{\eta} B(d|\Theta(\mathbf{s}), \eta) \left[1 - \sum_{t=1}^{n\delta} \Pr(\eta_j(\mathcal{N}^U) = t | g_{ij} = 1) \frac{\gamma}{t} \right]^d,$$

and clearly the probability that i gets at least an indirect offer is $\Psi_i^{in}(s_i, \mathbf{s}_{-i}) = 1 - \phi_i^{in}(s_i, \mathbf{s}_{-i})$. In a large labor market, this is equal to

$$(19) \quad \Psi^{in}(s_i, \mathbf{s}_{-i}) = 1 - e^{-\frac{\gamma(1-\delta)(1-a)}{\delta} \frac{s_i}{s} (1-e^{-s\delta}) \Theta(\mathbf{s})}.$$

In a symmetric profile where $s_i = s$ for all $i \in \mathcal{N}$, the probability that an unemployed worker hears a job indirectly is non monotonic in socialization effort and the intuition follows from the effect of indirect information flow which we have discussed above.

Finally, the overall probability that an unemployed worker gets at least an offer in a symmetric profile is:

$$(20) \quad \tilde{\Psi}^{in}(s) = 1 - \phi(s)\phi^{in}(s) = 1 - e^{-\frac{1-\delta}{\delta} (1-e^{-s\delta}) (a + \gamma(1-a)\Theta(s))}.$$

The network matching rate is decreasing in the decay of information flow and under full decay we are back to the network matching rate (5) developed in Section 3. Under indirect information flow, the expected utility of a worker i choosing s_i and facing a strategy of others $s_j = s$ for all $j \neq i$ is:

$$EU_i(s_i, \mathbf{s}_{-i}) = 1 - \delta(1-a)\phi_i(s_i, \mathbf{s}_{-i})\phi^{in}(s_i, \mathbf{s}_{-i}) - cs_i.$$

Proposition 5 *Consider a large labor market and consider indirect information flow. An interior equilibrium exists if and only if $c < ab(1-a)(1-a)$. In a symmetric interior equilibrium every worker chooses \hat{s} which is the unique solution to:*

$$(21) \quad \frac{(1-\delta)(1-a)}{\hat{s}} \left(1 - e^{-\hat{s}\delta} \right) (a + \gamma(1-a)\Theta(\hat{s})) \left(1 - \tilde{\Psi}^{in}(\hat{s}) \right) = c.$$

Proof of Proposition 5 Equilibrium condition (21) is obtained by taking the partial derivatives of $EU_i(s_i, \mathbf{s}_{-i})$ with respect to s_i and imposing symmetry, i.e., $s_j = s$ for all $j \in \mathcal{N}$. We now show that a solution exists and it is unique if and only if $c < a\delta(1-a)(1-\delta)$. To see this note that when $s \rightarrow 0$ the LHS of (21) equals $a\delta(1-a)(1-\delta)$ and when $s \rightarrow \infty$ the LHS of (21) equals 0. So, it is sufficient to show that the LHS of (21) is decreasing in s , which we now prove. We first claim that the following expression is decreasing in s :

$$\frac{1}{s} \left(1 - e^{-s\delta} \right) (a + \gamma(1-a)\Theta(s)).$$

Taking the derivatives of the above expression with respect to s we have that

$$\frac{1}{s^2} \left[-(a + \gamma(1-a)\Theta(s))(1 - e^{-s\delta}(1-\delta)) + (1 - e^{-s\delta})\gamma(1-a)\frac{\partial\Theta(s)}{\partial s} \right].$$

Since $\frac{\partial\Theta}{\partial s}(s) = (1 - \Theta(s))a(e^{-s} - \delta e^{-s\delta})$, then the above derivative is negative if and only if

$$\gamma(1-a)a(1 - \Theta(s))(1 - e^{-s\delta}) \left(e^{-s} - \delta e^{-s\delta} \right) < (a + \gamma(1-a)\Theta(s))(1 - e^{-s\delta}(1-\delta)).$$

Since the RHS of the inequality is always positive, if $(e^{-s} - \delta e^{-s\delta}) < 0$ the claim follows. So, suppose that $(e^{-s} - \delta e^{-s\delta}) > 0$. Here note that

$$1 - e^{-s\delta}(1-\delta) > (1 - e^{-s\delta}) \left(e^{-s} - \delta e^{-s\delta} \right),$$

if and only if, taking the log, $\ln(1-\delta) + s\delta > 0$ which is obviously true. Next, note that $a + \gamma(1-a)\Theta(s) > \gamma(1-a)a(1 - \Theta(s))$ if and only if $a + \gamma[\Theta(s) - a(1 - \Theta(s))] > 0$, which holds because $a + \gamma[\Theta(s) - a(1 - \Theta(s))] > a(1 - \gamma(1-a)) > 0$. These two observations imply our first claim. Using similar arguments, it is easy to show that $(1 - \tilde{\Psi}^{in}(s))$ is also decreasing in s . Hence, the LHS of expression (21) is decreasing in s . Proposition 5 follows. \blacksquare

To conclude, note that (21) is the same as (6) but for the fact that the job network supply is $(1 - \delta)(a + \delta(1-a)\Theta(\hat{s}))$ instead of $a(1 - \delta)$ as in the baseline model. But both are decreasing in δ ,

and, as a result, the comparative statics with respect to δ does not change.

A.3. Robustness Empirical Analysis.

Tables 4 and 5 show that the results described in Table 2 and 3 of Section 4 are robust to longer time spans aggregation of the data, i.e., five years averages instead of one year averages. Tables 6 and 7 replicate the analysis in Table 3 separately for the three skills groups and show that the positive and concave relationship between network investment and network matching rate, and job separation rate, is also present when we exploit variation across regions within workers with an homogenous educational attainment.

Table 4: Linear probability model regressing the proportion of job seekers using friends and relatives as the main job search method and the proportion of workers that found a job via their social networks against the job separation rate by region of residence, 5 years averages.

	Network Investment		Network Matching Rate	
	Job Seekers	Unemployed Job Seekers	Job Seekers	Unemployed Job Seekers
δ_t	6.215 (5.433)	6.013 (5.576)	21.109*** (7.187)	22.196*** (6.916)
δ_t^2	-68.640 (77.713)	-65.727 (74.899)	-283.691*** (94.016)	-297.611*** (99.368)
Dummy 2000 – 2005	-0.022*** (0.006)	-0.021*** (0.006)	-0.020** (0.008)	-0.017** (0.008)
R^2	0.447	0.423	0.446	0.426
Adj. R^2	0.401	0.374	0.400	0.379
Obs.	40	40	40	40

Source: UK QLFS, all male respondents, aged 16-64, waves from 1995 to 2004.

Standard errors bootstrapped using 1000 repetitions, in parenthesis. *** $p < .01$, ** $p < .05$, * $p < .1$.

Table 5: Linear probability model regressing the proportion of job seekers using friends and relatives as the main job search method and the proportion of workers that found a job via their social networks against the job separation rate by skill level and region of residence, 5 years averages.

	Network Investment		Network Matching Rate	
	Job Seekers	Unemployed Job Seekers	Job Seekers	Unemployed Job Seekers
δ_t	2.889*** (0.616)	2.511*** (0.686)	7.507*** (1.274)	7.533*** (1.414)
δ_t^2	-21.072*** (7.102)	-17.570** (8.124)	-53.907*** (14.592)	-54.882*** (16.051)
Dummy 2000 – 2005	-0.018*** (0.005)	-0.017*** (0.006)	-0.012 (0.010)	-0.012 (0.012)
R^2	0.356	0.302	0.435	0.393
Adj. R^2	0.339	0.284	0.420	0.378
Obs.	120	120	120	120

Source: UK QLFS, all male respondents, aged 16-64, waves from 1995 to 2004.

Standard errors bootstrapped using 1000 repetitions, in parenthesis. *** $p < .01$, ** $p < .05$, * $p < .1$.

Table 6: Linear probability model regressing the proportion of job seekers using friends and relatives as the main job search method against the job separation rate by region of residence for different skill levels.

	Low Skilled		Medium Skilled		High Skilled	
δ_t	1.977** (0.825)	3.244*** (0.716)	2.907** (1.220)	2.961** (1.218)	0.950 (1.079)	0.632 (1.180)
δ_t^2	-15.671** (7.197)	-23.736*** (6.093)	-22.055 (20.239)	-26.015 (19.514)	-15.527 (19.587)	-9.578 (21.217)
Year Dummies	No	Yes	No	Yes	No	Yes
R^2	0.036	0.293	0.160	0.290	0.004	0.034
Adj. R^2	0.026	0.252	0.152	0.248	-0.006	-0.022
Obs.	200	200	200	200	200	200

Source: UK QLFS, all male respondents, aged 16–64, waves from 1995:Q1 to 2004:Q4.

Standard errors bootstrapped using 1000 repetitions, in parenthesis. *** $p < .01$, ** $p < .05$, * $p < .1$.

Table 7: Linear probability model regressing the proportion of workers that found a job via friends and relatives against the job separation rate by region of residence for different skill levels.

	Low Skilled		Medium Skilled		High Skilled	
δ_t	3.476** (1.393)	4.438*** (1.454)	5.242*** (1.880)	5.403*** (1.826)	4.175** (1.813)	5.380*** (1.733)
δ_t^2	-24.615** (11.905)	-31.096** (13.126)	-60.431** (30.520)	-66.135** (29.225)	-92.919*** (34.283)	-111.936*** (32.994)
Year Dummies	No	Yes	No	Yes	No	Yes
R^2	0.066	0.186	0.077	0.123	0.047	0.113
Adj. R^2	0.057	0.138	0.068	0.072	0.037	0.062
Obs.	200	200	200	200	200	200

Source: UK QLFS, all male respondents, aged 16-64, waves from 1995:Q1 to 2004:Q4.

Standard errors bootstrapped using 1000 repetitions, in parenthesis. *** $p < .01$, ** $p < .05$, * $p < .1$.

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