Social networks, job mobility and industry evolution

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First draft, please do not quote.

Abstract

In this paper I present a model that was built in order to analyse the interdependencies between labour market dynamics and the evolution of industries' structure, in situations where interpersonal links among workers influence individuals' job decisions. The model was inspired by the case of industries that rely heavily on highly skilled labour and in which problems of incomplete information abound. The causal mechanisms here proposed constitute an alternative explanation for a number of well-known regularities of industry evolution and of labour mobility, being arguably more suitable to the analysis of those industries than the formal models available in the literature.

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1. INTRODUCTION

Industrial evolution and labour market dynamics are two fields of economic research which have developed fast in the past two decades. In both cases such development was very much related with the increased availability of micro data, and of statistic and econometric tools suitable to their treatment; and these, in turn, have favoured the identification of a number of empirical regularities (which are often taken as 'stylised facts' in both domains). Partly as a consequence, new theoretical models were proposed, aiming at explaining the regularities found in the data. There are even cases of authors who have worked in both fields, either on the theoretical front (e.g., Jovanovic, 1979, 1982) or on the empirical one (Addison and Portugal, 2002; Mata and Portugal, 2004).

Notwithstanding, the development of those two fields of research has been essentially parallel in nature. The most quoted models of industrial dynamics (for surveys see, e.g., Dosi et al., 1997; Sutton, 1997; Caves, 1998) tend to focus on the technological or financial determinants of changes in the structure of industries. In the same vein, the reference models of labour mobility and job matching (for a survey see, e.g., Farber, 1999) typically underestimate the mutual influence between industry dynamics and labour market forces.

And, however, it is not a surprise that changes in industries' structure and worker mobility mutually influence each other in many different ways, though not always in the most obvious ones. For example, some of the most influential empirical papers on industrial dynamics (e.g., Dunne et al, 1988, 1989; Evans, 1988) have noted that gross creation and destruction of jobs were associated with the dynamics of industries, though the proportion of job creation and destruction is significantly lower that the associate proportion of firm entry and exit (which is explained by the fact that entry and exit typically occur at low firm sizes). Moreover, as Haveman (1995) has pointed out, industry turbulence affects the labour markets not only directly (when individuals employed in established firms move to newly created ones, and individuals employed in dissolved or merged organizations move to surviving ones), but also indirectly, through the vacancy chains that are opened and closed by firms' founding and failure. This does not mean, however, that the relation between firms' growth and job flows is a monotonic one; Albaek and Sorensen (1998) have shown that the quit rate is not

affected by the amount of employment growth at the firm level (a large amount of separations occurs in expanding plants, suggesting that workers are leaving to obtain better jobs matches), and, symmetrically, that hiring occurs even in contracting firms, although at lower rates. In any case, it is not only the dynamics of industries that affect job flows, but also the reverse; for example, several recent studies analyse how the survival prospects of new firms are affected by the prior experience of their founders (Helfat and Liberman, 2002; Geroski et al., 2003; Eriksson and Kuhn, 2004; Dahl and Reichstein, 2005), drawing attention to the impact of workers' mobility between potentially competing firms for the patterns of industry evolution.

Nevertheless, in spite of all those evidences on the interdependency between industry evolution and labour market dynamics, there remains a lack of systematic discussion (both theoretical and empirical) about the details of such co-evolution and its implications.

This is not without relevance, especially when we realize that such interdependency can be crucial in many real world industries. In fact, historical accounts of specific industries often show that the patterns of firms' evolution and of labour force mobility are intrinsically related, particularly in the case of those services industries which are highly dependent on a specialized labour force. For example, in a paper on the evolution of the IT consultancy industry in Portugal (Mamede, 2002) I have suggested that the growth of firms was very much affected by their capacity to recruit new specialists and to avoid poaching by competitors. I have also suggested that the general level of employee's skills strongly influences the quality of the services provided, and therefore firms' reputation and their prospects for future growth. The same conclusions are usually drawn from other studies on professional services industries (see Gallouj and Gallouj, 1996).

When this is the case, models of industry evolution which ignore the role of labour market dynamics, and models of job mobility which abstract from the competitive pressures in which employers are involved, risk missing the main elements of the dynamic picture they propose to explain.

In this paper I present a model that was built in order to analyse the interdependencies between labour market dynamics and the evolution of industries' structure, in situations where individuals' job decisions are influenced by interpersonal links among workers.

The fact that social networks can, and often do, influence the dynamics of labour market has been recurrently emphasized by economic sociologists, following the work by Granovetter (1988, 1995). Studies within this tradition have revealed that employers and employees tend to know (or, at least, have information about) each other even before the beginning of their labour relation. These previous interpersonal links often influence individuals' job trajectories in several ways: social networks are an effective distribution channel of information about job opportunities, information given by personal acquaintances about the nature of a job are often taken to be more detailed and exact (and therefore more reliable), friends may facilitate individual integration and learning in organizations, having personal acquaintances among colleagues can facilitate the access to promotion and other discretionary benefits (especially, if those acquaintances are well positioned in the organizational power structure, and if contracts are more difficult be drawn exhaustively and to be enforced).

Previous contacts can exist due to reasons unrelated to the workings of the labour market, but they can also be a by-product of professional activity. As Cattani et al. (2002) suggest, the migration of individuals between organizations alters the webs of social relationships, both internal and external, with consequences over the performance of firms. In particular, when an individual leaves an organization she takes with her relevant knowledge about clients, technologies, organizational designs, access to resources (financial, material, and human), which can have disruptive effects in that organization (and significant benefits to her new employer).

The model I propose here is particularly suited to analyse the co-evolution of social networks, job flows and industry structure. Being inspired by the case of consultancy services, the model takes into account some other features typically found in those industries.

To start with, problems of incomplete information are pervasive in those industries. Consultancy is a highly idiosyncratic process in which the employees of both the services providing firms and of the client organizations interact extensively, and the outcomes of which strongly depend on the quality of the interactions between the personnel of both organizations. Given the relevance of idiosyncratic elements for performance, the relevant individual skills are not easily assessed on the basis of diplomas or other certificates. Moreover, consulting projects are most of the times a work done by teams of specialists, and it is often the case that firms are not able to differentiate between the individual contributions of each of the members involved. These features have two important implications: first, employers have to rely on less than perfect proxies of individual skills – such as individuals' past job trajectories; second, individuals are typically not paid on the basis of their individual productivity – performance prizes that compensate the several members of the teams without discriminating on the basis of individual efforts are a common feature in the industry (giving an incentive for individuals to move to the best performing firms, where collective prizes are expected to be higher).

In the absence of such uncertainty, the outcome of the industry's evolution would be very straightforward: the most successful firms would employ the most skilled specialists and would unequivocally grow (and possibly eliminate all the rivals). Introducing information incompleteness in the functioning of the labour markets has a number of implications, which the model presented below allows to analyse.

The next section of the paper presents the model. In section 3 the main results of the simulation are discussed. Section 4 sums up the conclusions and implications.

2. THE MODEL

There are only two types of agents in the model: firms and specialised workers (or specialists). Firms provide consultancy services to the market, while specialists are employed by those firms. The consultancy services are assumed to be in high demand, so the size of the industry is constrained only by the number of specialists available. In what follows I present the assumptions concerning the decisions of firms and

individuals, the role of social networks, the functioning of the labour market, and the dynamics of the industry.

2.1. The decision of firms

The model assumes that firms aim at earning higher profits. Profits increase monotonically with the scale of services provision (i.e., the size of the firm) and with the fees charged by the services provided.

The size of a firm is given by the number of specialists in its payroll. Since profits increase with size, firms want to grow as much as possible and they do so by recruiting more specialists. The model imposes restrictions on the growth of firms, assuming that the pace of growth can be faster for smaller firms than for larger ones[1]. The maximum number of job contracts each firm can perform at each period, MC_{jt}, is fixed according to the following equation:

$$(1) \qquad MC_{jt} = [N_{jt-1} * \delta] + 1$$

where N_{jt} is the number of employees of firm *j* at time *t*, and $\delta > 1$ is a growth rate parameter.

The level of fees per specialists is assumed to be dependent on the firm's performance in the previous period. The performance of firm *j* at period *t*, PF_{jt}, is defined as the average real skills of the firm's employees, that is:

$$(2) \qquad PF_{jt} = \Sigma RS^{j}_{it} / N_{jt}$$

where N_{jt} is the number of individuals working for firm *j* at time *t*, and RS^{j}_{it} represents the real skills of individual *i* who is working for firm *j* at time *t*. Individuals' real skills are assumed to be identically and independently distributed, according to a normal probability function, at the beginning of the simulation, and to stay fixed thereafter.

[1] This is in accordance with most empirical findings concerning the so-called Gibrat's law of proportionate effects (see surveys by Caves, 1998; Dosi et al., 1997; Sutton, 1997).

Since performance contributes positively to profits, and since the former is determined by the average level of specialists' real skills, firms' are interested in recruiting the most skilled individuals. However, it is assumed that individuals' real skills cannot be directly observed by the market. In order to assess individuals' skills, firms take into account the performance of the firms in which the individual has worked in the past. Accordingly, the skills individual *i* is expected to hold at time *t* are given by the equation:

$$(3) \qquad ES_{it} = ES_{it-1}*\beta + PF_{ijt-1}*(1-\beta)$$

where $\beta \in [0,1]$ is the autocorrelation factor of individuals' expected skills (it is the same for all individuals), and PF_{ijt-1} is the performance of the firm (*j*) employing individual *i* at time *t*.

For the sake of simplicity, I assume that there are no costs to the firms except for the wages paid to specialists. Furthermore, it is assumed that, in this industry, specialists' wages are a function of individuals' expected skills, and that the fees per worker paid by clients are more than enough for firms to cover their wage costs. The difference between total revenues and total wage costs is partially used by firms to give performance prizes to their employees. This has implications for individuals' choices, as will become immediately clear.

2.2. The decision of individuals and the role of social networks

Individuals prefer to work for firms with a better performance, and this is so for two cumulative reasons: first, their immediate financial benefits tend to be higher due to the fact that firms which perform better pay higher performance prizes; second, since specialists are paid according to their expected skills, and since the latter depend on the performance of the firms they have worked for in the past, they have an additional incentive to work for firms which show high performance levels.

However, in assessing the value of working for each firm, it is assumed that individuals consider not only the performance of that firm, but also the number of links they have with other specialists working for the same firm, according to the equation:

$$(4) \qquad V^i_{jt} = PF_{jt-1} * [1 + FF(\alpha, NL^i_{jt-1})]$$

where V^i_{jt} is the value to individual *i* of working for firm *j* at time *t*, PF_{jt-1} is the performance of firm *j* at time *t*, and $FF(\alpha, NL^i_{jt-1})$ is a function specifying the impact of interpersonal links on individual's *i* valuation of firm *j* as an employer (henceforth, the 'friendship function').

Three alternative specifications of the 'friendship function' are considered in the simulations – a linear form, a logarithmic form, and an exponential form – and they are represented by the following equations:

$$(5) \qquad FF(\alpha, NL^i_{jt-1}) = \alpha * NL^i_{jt-1}$$

$$(5') \qquad FF(\alpha, NL^i_{jt-1}) = \alpha * Ln(NL^i_{jt-1}+1)$$

$$(5'') \qquad FF(\alpha, NL^i_{jt-1}) = \alpha * exp(NL^i_{jt-1})^{1/2}$$

In all three equations, $\alpha>0$ (henceforth, the 'link value' parameter) determines the inclination of each curve, *Ln* represents the natural logarithmic function, *exp* stands for the natural exponential function, and NL^i_{jt-1} is the number of individuals among those working for firm *j* who are linked to *i* at time *t*. [2]

In words, when assessing the value of working for a certain firm, each individual takes into account that firm's performance level and adds to this value some percentage points for each link he has among the firm's employees. Given any two firms with identical performance levels, an individual prefers to work to the firm in which he has a higher number of personal links. When the linear 'friendship function' is used, the marginal value of each link is constant, irrespectively of the number of links the individual already has among the firm's employees. The logarithmic 'friendship function' implies instead the assumption that individuals value much more the first links they established

[2] In the logarithmic function, 1 was added inside the parenthesis in order to avoid negative values. In the exponential function the value in the parenthesis was squared rooted in order the smooth the function.

within a firm, than the additional links they establish after being densely networked to the firm's employees. The opposite assumption underlies the exponential 'friendship function'.

Links between individual specialists are established as a by-product of labour market flows. That is, in each period, for every pair of individuals currently working for the same firm, there is a chance that a social link is established (in case those individuals were not yet previously linked). The probability of two not yet linked colleagues becoming friends (conceptualized as a Bernoulli trial) is a decreasing function of the size of the employing firm[3]; more specifically, the probability that a link is established between any two specialists *i* and *k*, working for firm *j* at period *t* (and who were not previously linked), is given by:

(6) p('a link is established between *i* and *k*') = $1/N_{jt}$

where N_{jt} is the number of specialists employed by *i* and *k*'s employer at time t. A link between any two individuals will hold regardless of their future job trajectories

2.3. The job matching mechanism

Let me summarize what was stated above. Firms want to recruit as many specialists as possible, and want to attract the best specialists in the market. In this intent they face a number of constraints: first, the total number of specialists available in the market is limited by a certain amount, so firms compete among them in recruitment; second, firms are not able to assess the real skills of specialists, and have to take expected skills as an approximation to their real value; third, the model imposes a limit to the growth rate of firms per period. On the other side of the market, specialists are willing to work for firms with good technical performances and which employ a high number of specialists' personal links. On this, prospective specialists face as well a basic constraint: firms have a limited number of job positions to fill, and therefore only the specialists with the highest levels of expected skills will be recruited by the most desirable firms.

[3] The intuition behind this is that as firms get bigger it gets harder for personal contacts among any two of its employees to be established.

The job matching is done in the following way. Every period the labour market opens up. The list of specialists in the market is sorted in decreasing order of their expected skills and, for each individual, the list of firms is sorted in decreasing order of their value as employers. The first specialist in the list of individuals is allocated to the first job vacancy available, starting from the firm he values the most as an employer, and following the sorted list of firms; when the matching between the first individual and his preferred job vacancy has been achieved, the process is repeated for the other individuals in the list, following the ranking of expected skills, until all specialists have been allocated to some firm[4].

2.4. Entry and exit of firms

In the beginning of the simulation there are no firms. From then on, at each simulation step, a new firm enters the market. One individual (the entrepreneur) is randomly picked among all the specialists, and allocated to the new firm.

While incumbents are evaluated by prospective employees on the basis of their past performance (together with the personal links prospective employees have with current employees), new firms can only be assessed on the basis on their entrepreneurs' skills. Therefore, the model assumes that specialists' expectations on new firms' performance correspond to the expected skills of those firms' entrepreneurs. The expected skills of those individuals who have not yet been employed are equal to the mean value of the distribution of real skills.

As a consequence, in the first step of the simulation specialists will be randomly ranked and a given number of them will be allocated to the first firm entering the market[5]. But since individuals' real skills differ, from the very first simulation steps firms will display different performance levels, will be differently involved in the network of personal links, and will accordingly start to differ in their capacity to recruit specialists.

[4] Since firms are assumed to be willing to grow as much as possible (given some constraints in the pace of growth), after a few number of iterations there will be no unemployed specialists.

[5] The maximum number of initial vacancies is a parameter of the model.

On the other hand, specialists will immediately start to differ in their expected skills according to the firms they have been working for.

Along the process, some firms will grow and others will shrink. When incumbent firms loose all its employees, or when a new firm is not able to recruit any specialist besides its founder for two subsequent periods, they exit the industry (in the case of unsuccessful entries, the new firms' entrepreneurs will re-enter the labour market, and eventually be recruited by an incumbent firm).

I turn now to the analysis of the possible outcomes of such dynamics.

3. THE RESULTS OF THE SIMULATION

The main aim of the model which was presented in section 3 is the study of the possible interdependencies between labour market dynamics and industry structures. In order to do that I focus on the analysis of changes in some elements of the model, while others are left unchanged.

In all the simulation runs both the number of specialists and the number of periods (which determines the number of firms entering the market) was fixed at 250[6]. The mean of the distribution of individuals' real skills was normalised to 1 and the standard deviation was fixed at 0,25. The autocorrelation factor of individuals' expected skills (parameter β in equation 3) was fixed at 0,9. The initial maximum scale of potential entrants was fixed at 3, and the growth rate parameter (δ in equation 1) was fixed at 1,05. Moderate changes in these values do not modify the main conclusions to be drawn below.

In order to avoid unnecessary complications, and given the aim of the present model, the focus in the analysis of simulation outcomes is restricted to variations in (i) the value individuals attach to links with other specialists when assessing firms as potential

[6] This choice was determined by the constraints imposed by the software used for the analysis of the results.

employers (parameter α in equations 5, 5' and 5''), and (ii) the functional form of the 'friendship function' (same equations).

Each simulation for each set of values of these parameters was repeated 50 times in order to test the robustness of the results. A table displaying the means and coefficients of variation of selected indicators over the 50 runs of each parameterization is presented in annex.

The main indicators used in the analysis were the following[7]:

final number of incumbents:	includes all firms who employ more than 1 individual at the final step of the simulation;
four-firm concentration ratio:	it is the combined market share of the four largest firms in the industry (ranging from 0 to 100) (CR4);
Hirshman-Herfindahl index:	it is the sum of squares of the market shares of all the firms in the market (ranging from 0 to 10.000) (HHI);
industry turbulence:	it is the sum of firm exits and entries divided by the total number of incumbents;
proportion of job changes:	it corresponds to the number of individuals who have moved to a new firm divided by the total employment;
network density:	it is the number of pairwise links that were established among individuals over the total number of possible pairwise links;
proportion of external links:	it is calculated in the same way as the network density, but it excludes from the denominator the links between individuals working for the same firm.

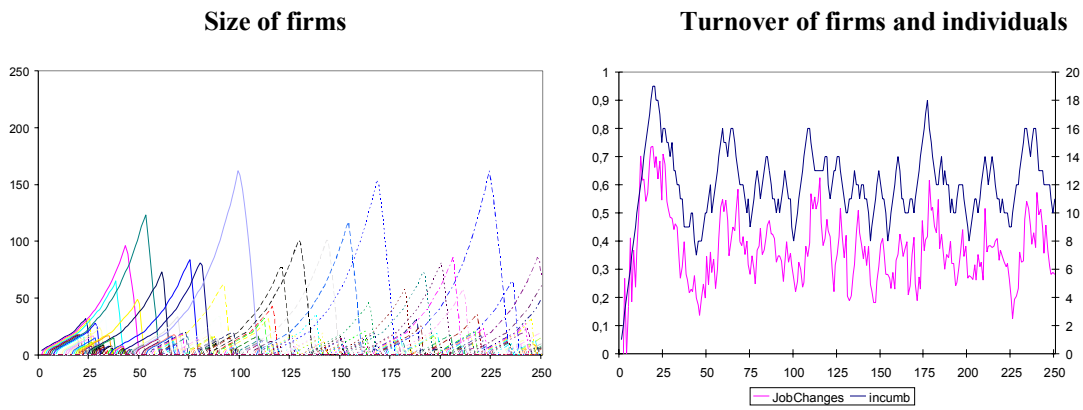
The remaining of this section presents the most relevant results of the simulation exercises.

[7] With the exception of the first one in the list, all indicators are computed at every step of the simulation.

3.1. The baseline model – irrelevance of interpersonal links

When specialists do not attach any value to interpersonal links (or when these are simply absent), individuals' job decisions are determined only by the performance of the firms in the market. That is, individuals will prefer to work to firms with the best performance possible. But since firms' performance levels are determined by the average value of real skills of their employees, the performance levels of firms will vary as they grow and as workers move from firm to firm. This gives rise to such dynamic patterns as the ones illustrated in Figure 1 below.

Figure 1 - Industry and labour market dynamics when links among individuals have no value



The graphs presented above illustrate the main patterns of industry evolution and labour market dynamics. On the left-side we have the evolution of firms' size, with the vertical axis measuring the number of employees. The right-side graph shows both the evolution in the number of incumbents and the proportion of individuals changing jobs at each period.

In Figure 1 we observe a situation of great instability, where firms grow quickly after they enter the market, until they reach a peak. After that point the number of employees rapidly decreases, and the firm eventually exits the market. It can also be noticed that the patterns of job mobility follow closely the evolution of incumbent firms: when the

number of incumbents is small, the proportion of employees moving to a different firm in each period is lower; contrarily, it is in the periods during which a higher number of firms is able to survive after entry that we observe the highest levels of job changes.

Such pattern has already been identified and discussed in a previous paper (Mamede, 2005). As was pointed out then, the cause for such behaviour resides on a paradoxical process in which competitive success is itself the cause of firms' failure. As a result of both the random process of firm creation (which leads to firms entering the market with varying levels of performance, depending on their entrepreneurs' skills) and the noisy job matching mechanism, a certain firm is able to sustain high levels of performance for a number of periods. Its superior performance allows it to hire more employees than the competitors, and consequently it grows above the average. Ideally, this firm would be able to identify the best specialists to hire, and the most skilled individuals in the market would want to be employed by such firm (since it would certainly be the best performing firm in the industry). But as the firm grows, since it cannot perfectly assess individuals' real skills, the firm will eventually start to hire specialists whose skills are below the firm's current average, and therefore its performance will start to decrease. The most direct competitors will soon surpass the firm's performance level and start to attract its employees, starting with the ones most valuable to the market (which tends to accelerate the process of declining performance and consequent shrinking). One of such competitors eventually becomes the biggest firm in the industry, and as it reaches its highest level of performance the same process happens again and again, until the end of the simulation.

Thus, the present case is one in which a combination of perfect employee mobility, incomplete information about individuals' skills, and absence of interpersonal links, gives rise to patterns of industry evolution and labour market dynamics characterized by great instability. In the following sections I discuss how such outcomes are changed as a result of individuals attaching value to interpersonal links when making their job decisions.[8]

[8] In Mamede (2005) I discuss the effects of introducing mobility costs in the context of a similar baseline model. It would also be interesting to analyse the consequences of changing the hypothesis on information (in)completeness in labour market decisions.

3.2. The value of interpersonal links (the linear case)

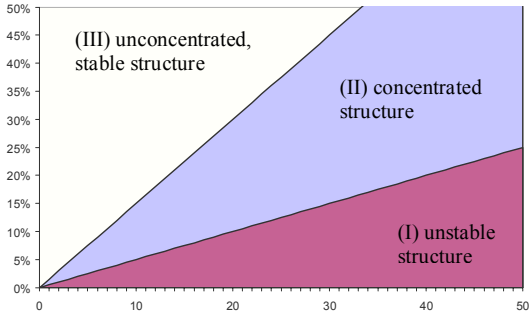
As explained in part 2 above, the worth of interpersonal links (henceforth referred to as 'link value') is here modelled in a straightforward fashion: given any two firms with identical performance levels, an individual prefers to work to the firm within which she has the highest number of personal links. In the next section I discuss the effects of different functional forms of the 'friendship function', while in the present section, for illustrative purposes, I consider the case of a linear function.

It should be clear what to expect in terms of individual decisions when we start considering the presence of valuable interpersonal links: as the industry evolves, individuals will establish links with some of the other employees working for the same firm; while the number of 'friendships' is low, interpersonal links should not prevent the mobility of workers between firms; but such links will subsist even if individuals move to different firms, and they will influence individuals' future job trajectories; firms employing a higher number of someone's 'friends' will become more attractive to that individual as potential employers; thus, we can expect to observe groups of friends ending up working for the same firms; furthermore, as interpersonal links are fostered inside firms, when individuals stay for longer periods in the same firm it becomes more probable that they establish links with all the others co-employees (namely, with those that did not influence the individual's initial decision to work there). In sum, introducing interpersonal links as a factor influencing individuals' job decisions is expected to bring about some stabilization in the evolution of industry structure.

As a matter of fact, this will be shown to be the case. Irrespectively of the functional form used to account for the value of interpersonal links, as the level of 'link value' increases, the proportion of individuals changing jobs at each period decreases and the industry becomes less turbulent (i.e., the number of incumbent firms stabilizes). The precise way in which that happens, and its consequences in terms of industry evolution and labour market dynamics is contingent on the combination of the levels of the 'link value' parameter and the specification of the 'friendship function'.

Figure 2 below illustrates how increases in the level of the 'link value' parameter affect the patterns of the industry's structural evolution, for the case of a linear 'friendship function'.

Figure 2 – The impact of changes in 'link value' on the patterns of industry evolution (linear 'friendship function')



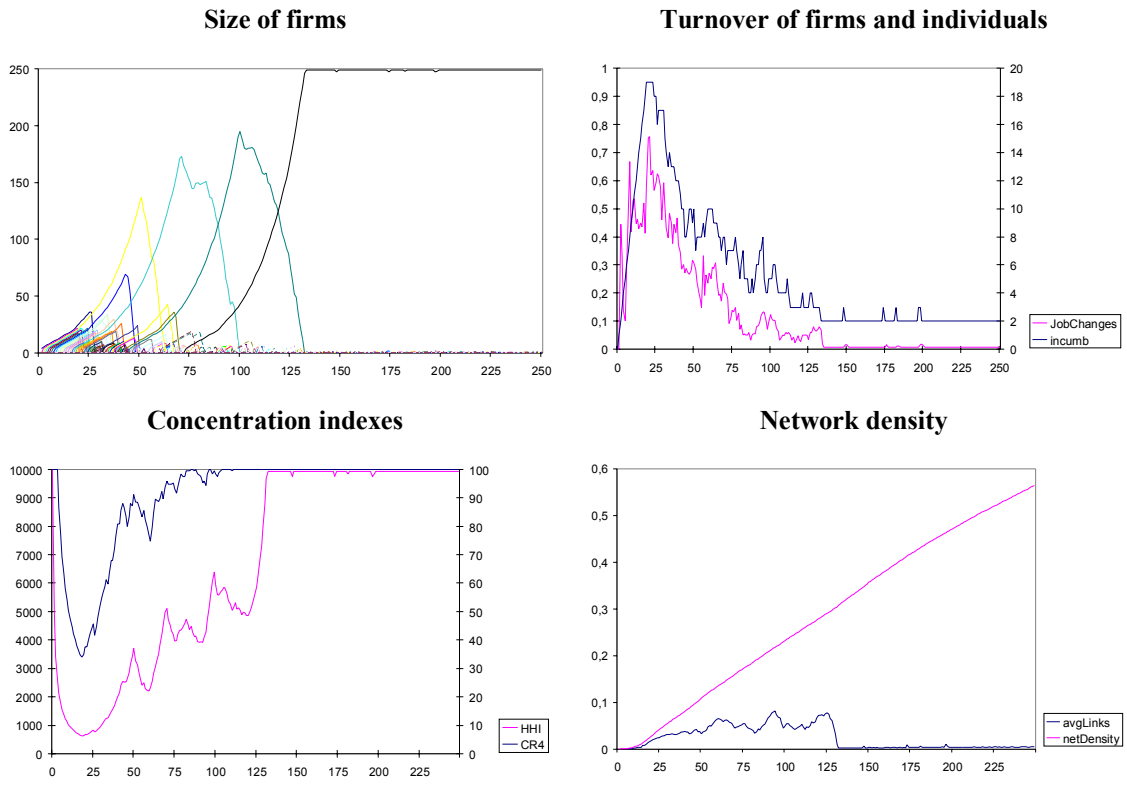
The graph above shows the impact of interpersonal links in an individual's assessment of a firm as a prospective employer: on the horizontal axis we have the number of 'links' among that firm's employees, and on the vertical axis we have the corresponding increase in the individual's valuation of that firm. The graph displays three distinct areas, which are delimited by two lines representing different levels of the 'link value' parameter. For example, the lower line corresponds to fixing the 'link value' at 0,5%; this means that, when evaluating a firm as prospective employer, an individual will add 5% to the level of that firm's performance if such firm employs 10 specialists to whom that individual is linked.

The areas shown in the graph represent three types of industry structure outcomes that are obtained as the level of 'link value' increases. As one could expect, for low levels of 'link value' (area I) the model does not behave differently from the case of valueless interpersonal links, which was discussed before.

However, above a certain threshold of the 'link value' parameter the model starts to reveal more stable dynamic patterns. For intermediate levels of the 'link value' parameter (approximately, in the range 0,5-1,5% - area II in Figure 2), after an initial

period of high incumbents' turbulence and frequent job changes, the industry stabilizes in a highly concentrated structure, typically a monopoly. Figure 3 below shows the main features of such situation.

Figure 3 - Industry and labour market dynamics for intermediate levels of the 'link value' parameter



In addition to the graphs displaying the firms' size and the turnover of firms and individuals (which were introduced in Figure 1 above), Figure 3 presents two other graphs. On the lower-left quadrant we have the CR4 and the HHI concentration indexes. The lower-right chart shows the evolution of the network density, together with the external links statistic (which only considers the links among individuals working for different firms, when calculating the network density).

Just as in the case of irrelevant interpersonal links, during the first half of the simulation run we can observe a recurrent situation in which some successful firm grows above the others for some periods, and then it invariably starts shrinking until it looses all its

employees. However, two main differences can be identified from the simple inspection of Figure 3: first, the successive leading firms are able to reach increasing scales and survive for longer periods; second, in this sequence of successive leaderships, at some point one firm is able to capture all the labour force, and from that moment onwards it becomes the indisputable monopolist.

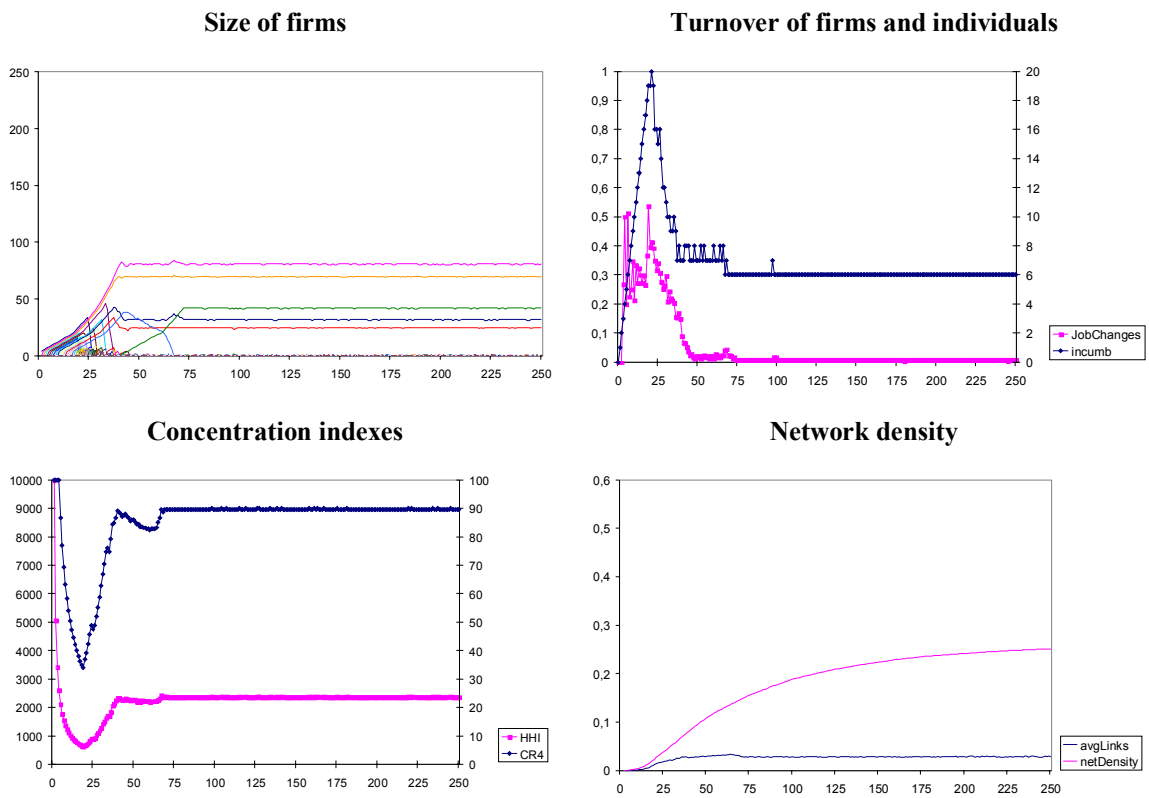
Again, it is immediately clear how the introduction of interpersonal link effects brings about this aggregate outcome. At every step of the industry evolution, new interpersonal links are being established among co-workers. As the number of links grows, they increasingly interfere in individuals' job decisions. During the initial stage of the process the number of links is not sufficiently high to avoid great job turnover; this allows the simultaneous presence of a relatively high number of incumbent firms, which operate in a rather unstable competitive environment (along the lines described before for the baseline simulation). But as the number of links grow, the 'friendship effect' will allow some firms to attract an increasingly high number of individuals to their ranks; the reverse of this is that it becomes ever more difficult for other firms to survive, leading to a 'shake-out' in the number of incumbents, soon after the industry has reached its highest number of operating firms. After some firm has become the dominant player in the industry (i.e., it captures at least 40% of the labour force), it takes very demanding conditions for another firm to overcome the dominant one.

In order to understand how changes in industry dominance can take place, one needs to take into account the fact that firms are not born equal; in fact, when they enter the market their initial performance is dependent on the skills of their first employees, in particular the ones of the founding entrepreneur. Furthermore, entrepreneurs are differently positioned in the network of interpersonal links, which means that, from the very beginning, firms are differently able to attract individuals and retain them in their ranks. After the industry's shake-out takes place, only firms that enter the market with very high performance levels and with considerable links to other firms' employees (preferably, highly skilled individuals) are able to survive. Still, these are necessary, but not sufficient conditions for survival. In fact, it may happen that a firm which enters the market with high performance levels and which benefits from numerous interpersonal links is nevertheless unlucky during the noisy job matching processes (i.e., in a number of successive periods the firm hires individuals whose skills are lower than expected).

In sum, for intermediate levels of the 'link value' parameter, as the selection conditions become tougher (due to the increasing density of interpersonal networks, especially within the dominant firms), firm survival demands not only superior characteristics (performance and network links), but also chance. At a certain stage the density of the network of interpersonal links is too strong for any entering firm to be able to capture employees to its ranks, and the industry stabilizes in a monopolistic structure.

Finally, for higher levels of the 'link value' parameter (approximately, for values above 1,5% – area III in Figure 2), we obtain less concentrated patterns of industry structure. In fact, after some threshold, further increases in the level of 'link value' imply an increase in the average number of incumbents and a corresponding decrease in the concentration ratios. Figure 4 below presents the typical outcome of a simulation when the 'link value' parameter is fixed at 2,5% (using the linear form of the 'friendship function').

Figure 4 - Industry and labour market dynamics for moderate levels of the 'link value' parameter



As can be seen in the graphs above, some of the dynamic patterns are common to the ones identified for intermediate levels of the 'link value parameter': once again we have an initial period during which many firms enter the market and are able to survive and grow for a number of periods, and during which individuals are changing jobs frequently; after that, some firms are able to grow above the others, attracting a high number of workers, and causing a shake-out in the number of incumbent firms. But the similarities with the previous case stop here. In fact, by comparing the graphs it can be noticed that the proportion of job changes in the initial period has decreased. This means that, as could be expected, interpersonal links start to influence individuals' job decision since the early evolution of the industry; as a result, individuals more easily 'get stuck' in a firm (which explains why the proportion of links external to the individuals' own employing firms is even lower than before – see chart in the bottom-right quadrant).

Consequently, firms which perform well enough in the early stage are more likely to survive, even if their performance levels decrease afterwards – since they can rely on the influence of interpersonal links among its employees to prevent poaching from competitors. The 'first-mover advantages' are not limited to the ability to retain present employees: firms that enter the market early and which maintain high levels of performance for a while are more able to attract individuals with high expected skills (and retain them in their ranks afterwards).

However, such 'first-mover advantages' are not absolute. As illustrated in Figure 4, even firms which attempt to enter the industry after the shake-out episode may be able to grow and survive. This is because the successful incumbents tend to reduce their performance levels as they grow; just as in the case where interpersonal links were irrelevant (see Figure 1), growth is a source of risk to firms, since in order to grow firms have to hire individuals whose skills may be lower than the firms' current average (and in fact this can be expected to happen after some point, since firms start by hiring those individuals whose expected skills are highest). But in the present case, the 'risk of growth' is not as high as before, since firms can rely on the network of interpersonal links. That is, market leaders can afford to have lower performance levels than competitors. Therefore, as long as their entrepreneurs are highly skilled and have good

links to other workers, late-comers may still achieve a considerable competitive position.

But this is true only up to some point. After a number of periods the network of interpersonal links inside the firms is so dense that it becomes virtually impossible for prospective entrants to attract workers to their ranks. Every attempt by an entrepreneur to launch a new venture is doomed to failure (and those individuals tend to go back to their former employing firm, where the number of interpersonal links among the employees is highest).

If we increase even more the level of the 'link value' parameter, the result is that the average number of incumbents will increase even more: interpersonal links will start influencing the results even earlier in the industry's evolution, and firms will more easily retain employees, in spite of their relatively low performance. This also means that successful entry becomes more probable in later periods, since there will be more incumbent firms with low levels of performance, which can be challenged by 'late-comers'.

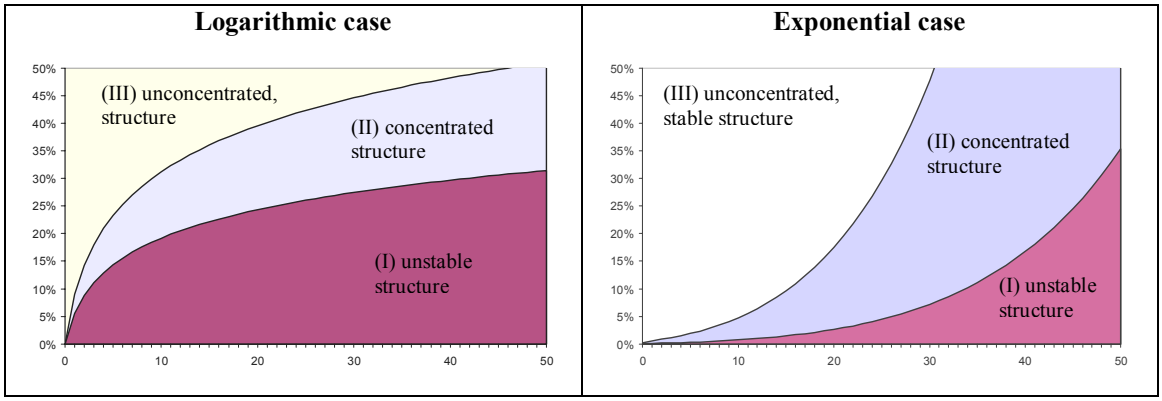
3.3. Logarithmic and Exponential 'friendship functions'

The results that have been presented and discussed in the last section refer to simulations in which the linear version of the 'friendship function' was used. This means that, when an individual is assessing a firm as a potential employer, the value of that firm to the individual is equal to the performance of the firm plus some constant percentage points for each link the individual has among the firm's employees. I.e., if the 'link value' parameter is fixed at 1%, an additional link with some of the firm's employees increases the value of that firm to the individual by exactly 1% of the performance level, no matter how many 'friends' the individual already has among that firm's employees.

Of course, this is not the only possible way for interpersonal links to influence individual job decisions. In the present section I discuss how the outcomes of the model change when two alternative versions of the 'friendship function' are adopted – the

exponential form and the logarithmic form. In the case of the exponential 'friendship function', the value an individual attaches to a firm as a potential employer increases much more for every new link with that firm when the individual already has many friends working there, than when the new link is the first to be established with that firm's employees. I.e., having few friends working for a firm does not make much difference, but having many friends who are employed there can make that firm much more attractive as a potential employer. The case of a logarithmic 'friendship function' is the inverse one: the difference in terms of individuals' valuation between having 1 or 2 links to a firm is much bigger than the difference of having, say, 10 or 11 links with the firm's employees. [9]

Figure 5 - Outcomes of alternative versions of the 'friendship function' for different levels of 'link value'



Like in the linear case, in both the exponential and the logarithmic versions of the 'friendship function' it is possible to identify three main types of outcomes for different levels of the 'link value' parameter (see Figure 5). Again, when the level of 'link value' is low (area I) the results of the simulation resemble the case of irrelevant interpersonal links; and when the 'link value' parameter is fixed at sufficiently high levels, the result

[9] One possible way to rationalize these alternative functional forms of the friendship function is the following. In the exponential case interpersonal links are relevant for reasons of power: having few friends in a firm does not alter one's career prospect, while having many friends in a firm grants an easier access to promotion and other benefits. In the logarithmic case, individuals are motivated by the pleasure of working with close friends; arguably, one's emotional comfort increases much more when switching from a job situation where there are no friends among the co-workers to one in which there is one or two friends, than when an individual already works with dozens of friends and makes an additional emotional link among his colleagues.

is a relatively stable, unconcentrated industry structure. Also as before, the lower-bound of the intermediate range of 'link value' levels (area II in the graphs above) typically results in highly concentrated industry structures, with an average HH index above 6000, which is typical of monopolistic (or quasi-monopolistic) industry structures; and 'link values' in the upper-bound of area II give rise to moderate concentrated structures, with an average HH index between 2000 and 6000 (see table A.1. in annex).

However, behind the similarities which result from those indicators, one can identify significant differences between alternative specifications of the 'friendship function' by analysing the details of the industry dynamics.

The most interesting case to emphasize is the behaviour of the Logarithmic 'friendship function' for intermediate levels of the 'link value' parameter. In both the Linear and the Exponential cases, as the 'link value' increases, there is a smooth transition from a stable monopoly (or quasi-monopoly), through different degrees of stable, relatively symmetric oligopolies (with decreasing levels of concentration), and finally to rather unconcentrated, stable industry structures. On the contrary, the Logarithmic case is much more unstable and rather unpredictable – as can be confirmed by the inspection of Table A.1. (in annex), which reveals that the levels of the coefficient of variation for intermediate levels of the 'link value' parameter are typically much higher in the Logarithmic case (for similar average values). While in most cases the main features of the industry dynamics are not substantially changed for different runs of the same parameterization, in the Logarithmic case, the set of possible outcomes for levels of 'link value' in the upper-bound of region II in Figure 5 is huge; in such cases, the same parameterization can give rise to very diverse results, which include: stable and unstable monopolies, oligopolies of different degrees (usually not totally stable) with or without a dominant firm, changes from one type of structure to another at different moments in the evolution of the industry, etc.

By now the mechanisms underlying the unpredictability of outcomes in the case of a Logarithmic 'friendship function' with moderate levels of 'link value' should be easy to understand. Essentially, in such conditions, it is much easier for a firm to enter the market successfully even after the 'shake-out' episode.

A numerical example may help to elucidate this: consider the case of an individual who is working for an incumbent firm, which has current performance level equal to 100, and which employs 20 other workers who are all linked to our individual; using a Logarithmic 'friendship function' with 'link value' equal to 13%, the value of this firm as an employer to our individual is approximately 140; now suppose that one of those 20 colleagues becomes an entrepreneur and starts a new firm; if the skills of this entrepreneur are equal to 130, even if this is the only friend our individual knows in the new firm, the value of the later as an employer will be $130*0.09 \approx 141$. I.e., even if the density of the network of interpersonal links inside a large, incumbent firm is very high, this will not necessarily prevent poaching by new competitors – especially if the new firm's entrepreneur is highly skilled and well positioned in the network.

It is also interesting to note that the unpredictability resulting from intermediate values of the Logarithmic 'friendship function' disappears as the level of the 'link value' parameter increases even more. The reason for this is the following: intermediate levels of 'link value' do not totally prevent the mobility of workers between firms in the initial stages of the industry's evolution (although average job changes are somewhat reduced, when compared to an equivalent parameterization of the linear case); even though individuals attach great value to their first friends, this is usually not enough to guarantee the survival of low performing firms; on the contrary, when the 'link value' is very high, as soon as a link is established within a firm, this will hardly ever exit the market, regardless of its performance. In rigour, for high 'link values', the very same process occurs with both other functional forms of the 'friendship function'.

Finally, it is worth to discuss why the Exponential form of the 'friendship function' does not give rise to significant different results of the Linear case. One should recall that in the Exponential case the effect of interpersonal links on individuals' job decisions is rather small until the industry has evolve enough for the social network to become sufficiently dense. This implies that in the initial stage of the industry's evolution interpersonal links are not playing a significant role, and the mobility of individuals between firms is higher. As the industry evolves, an increasing number of interpersonal links is being established, leading to a stabilization of the industry following the same lines as in the Linear case. From that moment on, the densification

of interpersonal links will happen basically inside the incumbent firms; since the impact of links is increasing with the densification of the network, further job changes become increasingly improbable. This helps to explain the very low levels of later turbulence in the Exponential case, even for moderate levels of the 'link value' parameter.

Figure 6 summarizes the essential aspects of the discussion put forward in this section.

Figure 6 - Comparing the Logarithmic and the Exponential 'friendship functions' with the Linear one

		Log	Exp
Final incumbents		=	=
CR4		=	=
HHI		+	=
Turbulence	**Initial**	=/-	=
	Later	++	--
Job changes	**Initial**	-	=/+
	Later	++	-
External links	**Initial**	--	=
	Later	=	=
Final density		=	=

4. DISCUSSION AND CONCLUSIONS

The model presented in this paper was built in order to analyse the interdependencies between labour market dynamics and the evolution of industries' structure, in situations where individuals' job decisions are influenced by interpersonal links among workers. One crucial motivation for the development its was the scarcity of models of industrial dynamics suitable to those industries that strongly depend on highly skilled workers,

and in which labour mobility can have significant impacts on the patterns of the industry's evolution.

I argued in the introduction that the existing models of industry evolution and of job mobility, because they ignore the co-evolution of the product and the labour markets, tend to miss some relevant elements of the industries mentioned above. It is now time to discuss how the model put forward in this paper can contribute to the analysis of such contexts.

I start by referring the prevailing theories of industries' life-cycle. Many industries have been found to follow some similar pattern along their development, in which the following are included (for an overview, see Klepper, 1997): in their initial stage of development industries grow fast, many firms enter the market offering their own products, few firms exit, and the number incumbents increases accordingly; as the industry evolves the industries' growth slows down, the entry rate decreases, and there is a shake-out in the total number of incumbents; after that, changes in the market share of leading firms become less frequent, entry and exits are strongly reduced, and the industry structure stabilizes.

Several different theories were suggested to explain these regularities. For example, in Abernathy and Utterback (1978), after an initial period of uncertainty in which several firms offer their product innovation, a dominant design emerges in the market, reducing the uncertainty about the future technological trajectories; this creates an incentive for firms to invest in cost-reducing innovations, and the firms who are less efficient in the production of the dominant design are driven out of the market. Klepper (1996) has reversed the direction of causality, suggesting that the emergence of a dominant design is a result of the shake-out, rather than being at its origin; and the causes for the shake-out are to be found elsewhere: they are related to the fact that cost-reducing investments are more rewarding for firms operating at larger scales; firms that grow first tend to have lower costs and drive others out of the market. After the shake-out, as prices decrease further and margins are compressed, the incentives to grow above the average will vanish, and the industry stabilizes. Jovanovic and McDonald (1994) propose still another explanation for the shake-out episode, based on the idea of an exogenous technological development to which only some firms are able to adapt successfully.

What those three alternative explanations have in common is the fact that they are based on the assumption that price is a crucial variable for firm's competitiveness. And while this is true for most industries, it is more relevant for some industries than to others.

As was shown in section 3, for many different sets of parameters, the model proposed here gives rise to the same regularities in the evolution of industries which were identified before, but it does that on the basis of quite different mechanisms. As in Klepper (1996), there are in my model some 'first-mover' advantages, but these are now related more with the dynamics of the network of interpersonal links than with any kind of durable superior performance; in fact, firms that perform well enough in the early stage are more likely to survive, even if their performance levels decrease afterwards – since they can rely on the influence of interpersonal links among its employees to attract new specialists and to prevent poaching from competitors. However, and again contrarily to Klepper's model, such 'first-mover advantages' are not permanent in the present case: as was shown, even firms which attempt to enter the industry after the shake-out episode may be able to grow and survive; this is because the established firms tend to reduce their performance levels as they grow (the paradoxical 'risk of success'), giving the opportunity for new firms to poach their employees (as long as this new firms reveal high performance levels and their entrepreneurs are well located in the network of interpersonal links). Still, such successful entries by late-comers become increasingly difficult, and this is explains the fact that the industry structure tends to stabilize after the shake-out.

The present model is also able to propose alternative explanations for the most commonly observed patterns of job mobility. Farber (1999) identifies three main regularities in this domain: (i) long job tenures are a common feature in most markets, (ii) most new jobs have a short duration, and (iii) the probability of job cessation decreases with tenure. Two main classes of models have been put forward to discuss such regularities. On one hand, we have models based on the idea of efficient matching between the workers' human capital and the specific capital of the firm. The other type of models is based on the notion of non-observable heterogeneity among workers, related with the individual propensity for job change. Both types of models have been able to successfully replicate the regularities mentioned above.

In the model presented in this paper the same regularities about job mobility are observed. But, again, the mechanisms suggested are to some extent distinct from the ones proposed by both matching models and model based on non-observable individual heterogeneity.

The short duration of many jobs is here related to two phenomena. First, they are a direct consequence of the entry and exit of firms in the first stage of the industry evolution (and of the indirect effects related to the vacancy chains). Second, they derive from the fact that, in the initial stage of the industry evolution, individuals are mainly driven by the will to work for high performing firms; but job mobility in this period is a self-reinforcing mechanism – the more individuals change jobs in the search for higher financial rewards, the more firms change their position in the ranking of performance, creating the conditions for further mobility.

However, as the industry evolves, a growing number of interpersonal links is established, and individuals' choices are increasingly influenced by them. The longer an individual stays in a firm, the higher the number of links she establishes with her colleagues and the less likely becomes the poaching by other firms.

It should go without saying that the appropriateness of these alternative explanations for understanding real world phenomena can only be assessed on a case-by-case basis. But it may be sensible to adequate the theoretical explanations to the specific contexts under analysis. This is what the present model attempts to do, having in mind the evolution of consultancy services, as well as other industries which strongly rely on the availability of highly skilled labour.

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A.1. - Main indicators used in the analysis*

	Link value	Final Inc.	CR4	HHI	Turbulence		Job Changes		External links		Final Density
					Initial	Later	Initial	Later	Initial	Later	
Linear	0.001	9,1	76	2518	0,18	0,18	0,45	0,29	0,02	0,12	0,40
		28	*3*	*11*	*6*	*11*	*8*	*14*	*9*	*9*	*5*
	0.005	1,7	93	6696	0,20	0,17	0,40	0,04	0,02	0,05	0,57
		38	*1*	*9*	*8*	*45*	*7*	*46*	*10*	*51*	*3*
	0.025	3,5	92	3168	0,19	0,00	0,23	0,01	0,02	0,02	0,33
		30	*4*	*32*	*14*	*231*	*8*	*9*	*9*	*16*	*23*
	0.125	13,6	44	921	0,08	0,00	0,10	0,01	0,00	0,00	0,08
		9	*7*	*7*	*5*	*253*	*7*	*58*	*28*	*26*	*9*
Logarithmic	0.01	9,6	75	2538	0,19	0,18	0,42	0,30	0,02	0,13	0,40
		27	*2*	*9*	*7*	*11*	*7*	*11*	*10*	*10*	*4*
	0.10	2,1	94	6165	0,21	0,10	0,20	0,03	0,01	0,07	0,55
		58	*1*	*18*	*15*	*45*	*10*	*35*	*11*	*37*	*11*
	0.13	3,7	87	4180	0,15	0,03	0,15	0,02	0,01	0,03	0,39
		62	*12*	*58*	*23*	*105*	*14*	*50*	*25*	*76*	*42*
	0.25	12,5	47	990	0,08	0,01	0,10	0,01	0,00	0,00	0,09
		13	*10*	*11*	*6*	*89*	*7*	*40*	*37*	*36*	*15*
Exponential	0.0003	9,1	72	2071	0,18	0,16	0,45	0,35	0,02	0,13	0,37
		26	*3*	*9*	*6*	*8*	*6*	*11*	*7*	*7*	*4*
	0.001	1,5	92	7084	0,19	0,01	0,43	0,01	0,02	0,01	0,56
		54	*1*	*15*	*8*	*210*	*8*	*43*	*10*	*111*	*9*
	0.01	3,4	93	3133	0,20	0,00	0,28	0,01	0,02	0,03	0,33
		24	*4*	*20*	*8*	*707*	*8*	*8*	*10*	*17*	*16*
	0.1	14,2	43	890	0,08	0,00	0,09	0,01	0,00	0,00	0,08
		10	*7*	*7*	*5*	*330*	*6*	*39*	*26*	*25*	*9*

* The values shown for the 'link value' parameter were chosen in order to make the different 'friendship functions comparable. In each cell there are two figures: the one on the top corresponds to the average value of the corresponding indicator; the one on the bottom is the coefficient of variation (the standard deviation as a percentage of the mean).