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On firm growth in networks

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Abstract

This paper is explorative in nature. Based on an empirical analysis of two different industrial settings (life sciences, LS; information and communication technologies, ICT), it investigates network growth and firm growth in networks. We find a remarkable correspondence between a few fundamental findings of the 'old' stochastic approach to the analysis of firm internal growth, and empirically observed patterns of firm external growth through collaborative agreements. We show that scale-free behavior in real-world industrial networks can be accounted for by a general and parsimonious model, originally developed by Herbert Simon in 1955, based on entry and proportional growth. However, relevant departures from the stochastic benchmark are revealed that cannot be ascribed to the effect of mergers and acquisitions (M&As) and growth autocorrelation. Moreover, different regimes of growth are found to be at work in the life sciences for originators versus developers of new business opportunities, reflecting the fact that growth is driven by specialization and division of labor in the processes of generation and attraction/development of technological opportunities.

Keywords: Firm growth; Network growth; Biotechnology; Information and communication technologies

1. Introduction

Division of innovative labor and R&D collaborative contractual relationships are recognized as increasingly important economic phenomena (see Arrow, 1983; Arora et al., 2001). In particular, networks of contractual relationships among firms specialized in research and exploration (*originators*) and firms focused on development, production, and commercialization (*developers*) are ever-widening organizational forms, especially in high-tech, knowledge-intensive fields (see Orsenigo et al., 2001).

In the last 10 years, several studies have shown that network structure and positions in networks influence firm performance and growth (Powell et al., 1996, 1999) and ultimately, market structure (Mc Lean and Padgett, 1997; Pammolli and Riccaboni, 2002). Moreover, most of the literature agrees that networks have to be analyzed as a distinct organizational solution for the access to outside knowledge sources, the coordination of heterogeneous learning processes by agents endowed by different skills, competencies, access to innovation, and assets (Pavitt, 2000).

A different stream of literature focuses on dyadic relationships within and between organizations and trade-offs defined at that level (Arrow, 1974; Williamson,1991): particularly the trade-off between economies from specialization exploited through task partitioning and the transaction costs involved in transferring knowledge and technological information through arm's length contracts (see Pisano, 1990; Teece, 1988, 1998; Arora et al., 2001).

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In general, despite a growing consensus on networks as a distinct organization form and on their importance in innovation, learning, and evolution (see Freeman, 1991), economic models of division of (innovative) labor tend to focus on either standing-alone organizations or dyadic contractual relationships. Correspondingly, the literature on firm growth considers firms as fixed, elementary, and independent unit of analysis to focus on the dynamic properties of a set of quantities associated with them (e.g. sales, employees, innovative outcome, value added). As a consequence, firms' structure, interactions, collaborations and transformations can hardly be accommodated in the usual dynamical system theoretical models.

Against this background, we aim at moving a step forward in the analysis of processes of growth in networks. We consider the links between *originators* and *developers* as instances of firm external growth. On the one side, *originators* discover new technological opportunities and establish contractual relationships that generate income and give access to relevant assets. On the other side, *developers* rely on collaborations with originators to get access to outside knowledge sources and capture new technological opportunities.

We represent size and growth in terms of firms' connectivity (k) as measured by the number of collaborations established, seen as independent business opportunities of size unity arising over time (see Ijiri and Simon, 1977). Our empirical investigations on growth in networks in the life sciences (LS) and information and communication technologies (ICT) offer a neat picture, revealing the existence of scaling phenomena, with the firm connectivity distribution being well described by a power law of the form $N = \alpha K^{-\gamma}$, where N is the number of firms with more than K connections.

This result, which is stunningly equivalent to well known empirical regularities on processes of growth in several domains of both natural and social sciences (see Simon, 1955; Albert and Barabási, 2001; Fujita et al., 1999), suggests that an apparently general phenomenon ought to be central in any modeling effort of firms, regions and networks growth.

Along this way, we focus on the mechanisms behind the dynamic properties of growing networks and on firm growth in networks, unraveling striking analogies between processes of internal growth and processes of external growth through collaborative agreements.

We do show that the scale-free behavior detected in networks of innovators can be accounted for by a very general and simple model, which is rooted in the 'old' stochastic approach to the analysis of firm growth.

While growing, networks in LS and ICT self-organize into scale-free structures shaped by entry of new firms and by proportional growth of the connectivity of individual firms, with remarkable departures from a regime of universal random growth.

In addition, departures from the Pareto distribution in the life sciences sector cannot be ascribed to 'traditional' explanatory variables (growth autocorrelation, mergers and acquisitions). In LS, different regimes of specialization and growth are found to be at work for originators versus developers, reflecting differences in the processes of generation versus absorption/development of technological opportunities.

In particular, the population of originators is characterized by a regime of proportional growth which corresponds to a 'popularity is attractive' mechanism (see also Zucker et al., 1998), while for developers this mechanism is attenuated by an additional random component.

While our preliminary results cannot be fully explained given the present status of our knowledge, they are highly coherent with an interpretation of firm growth and networking activities which is rooted in a competence-based view of organizational growth and division of labor (Penrose, 1995; Richardson, 1972; Nelson and Winter, 1982; Dosi, 2000).

The empirical findings presented in this paper—as well as in Orsenigo et al. (2001) and in Pammolli and Riccaboni (2002)—show that processes of network growth are sustained by dynamic complementarities between patterns of specialization in knowledge production (originators) and processes of diversification of in-house capabilities by large multi-product, multi-technological companies (developers, see also Granstrand et al., 1997; Pavitt, 2000).

Our analysis points to some basic principles behind the growth of firms in technological networks, providing a simple benchmark for future investigations. In addition, one important feature of our work is related to the fact that, since we are dealing with the dynamics of a set of links, we can exploit the duality of the overall system, extracting topological information which can be used to uncover the underlying causal data generating mechanisms. That is to say, the study of firm growth in systems of division of labor is important also because it enables plausible restrictions on the acceptable classes of conditional predictive distributions and on the dynamics of the processes which generated them, contributing to a better understanding of firm growth in general.

2. Firm growth and connectivity in networks

Both business size distributions and nodes degree[1] distributions of many real-world networks exhibit heavy tails and power law scaling of the form $P(k) \sim k^{-\gamma}$ (see Sutton, 1997; Brock, 1999; Albert and Barabási, 2001). The connectivity distributions of networks with complex topologies such as the World Wide Web, the Internet, protein networks, phone call and power networks, the movie actor collaboration network, the science collaboration graph, the web of human sexual contacts, the citation network of scientists, follow scale-free power laws, reflecting some major departures from a regime of 'universal' random growth (Barabási and Albert, 1999).

To make a long story short (see also Riccaboni, 2000), the origin of scale-free behaviors in networks can been accounted for by a simple model for scaling in growth processes that was proposed by Simon (1955), in order to give an interpretation of distributions such as word frequencies in texts or population figures of cities.

Simon models the dynamics of a system of elements with associated counters (business opportunities of size unity), where the dynamics of the system is based on constant growth via the addition of new elements (new business opportunities) as well as incrementing the counters at a rate proportional to their current values. On the one side, networks can grow by the addition of *new nodes* that become linked to existing ones. On the other side, networks growth can be driven by *new collaborations* established among existing nodes according to a popularity mechanism (preferential attachment).

Interestingly enough, these two mechanisms can be considered as particular instances of the model which was solved by Simon in his 1955 paper, in which the Pareto distribution is derived from "simple and economically plausible assumptions", namely size independence of percentage growth rate (the Gibrat's law of proportionate effect), and constancy of the entry rate. In particular, the original Simon model accounts for a robust empirical regularity that has been detected in many networks across different fields, irrespectively of their nature and components: that is, the probability distribution of the number k of links that point to a particular node (i.e. web page, scientist), $P(k)$, decays following a power law $P(k) \sim k^{-\gamma}$, with the scaling exponent γ being very close to 2, both for the distribution of in coming and out coming links (for a review, see Albert and Barabási, 2001).

Given the pervasiveness of scale-free distributions across different empirical domains, we retain the Pareto distribution as a benchmark. Then, we perform a simulative exercise aimed at exploring the existence of differences in growth dynamics for originators and developers, providing supplementary topological information to interpret mechanisms of division of innovative labor in the two sectors.

Ijiri and Simon have shown, in the case of business firm size, the existence of systematic departures from Pareto. Equivalently, the connectivity distributions in LS and in ICT depict flattened upper tails, suggesting equivalent departures from the Pareto law, with loosely connected nodes following a different distributional model (possibly Poisson, or a combination of Poisson and power law).

In the next section, however, we show that the mechanisms identified by Simon and colleagues to explain the observed departures from the Pareto size distribution—namely, M&As and growth autocorrelation—do not provide a comprehensive explanatory framework for the analysis of firm growth in networks.

In particular, we detect the existence of systematic differences between the curvatures of the connectivity distributions in LS versus ICT, which seem to be the outcome of inherently different technological and market regimes.

3. Firm growth in networks: empirical and simulative results

In this section, we refer to two domains, LS and ICT, in which networks of innovators have grown

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[1] The degree of a node is the number of ties incident to that node.

substantially in the last 20 years. Both sectors embrace a vast set of enabling technologies, with deep significant cross-sectoral impact on primary economic areas such as healthcare, environmental preservation, and nutrition for LS and hardware, software, telecommunications and Internet for ICT.

New bodies of knowledge have generated a plethora of scientific and technological opportunities, nurturing a continuous flow of entry of new firms, as well as an extensive division of innovative labor between *originators* and *developers* of R&D projects (Orsenigo et al., 2001).

The sustained growth of networks by the entry of new firms and by the addition of new collaborations has been driven by the evolution and combination of relevant scientific and technological knowledge bases. Both networks have grown considerably in the 1990s till 1999, when the general economic downturn slackened off their expansion. Interestingly enough, patterns of expansion of networks in LS and ICT differ considerably. The LS network has started in late 1970s and has been *linearly* and constantly expanding (see Orsenigo et al., 2001; Pammolli and Riccaboni, 2002). On the contrary, the ICT network took off at the beginning of the 1990s, have grown *exponentially* for 10 years and leveled out at the end of the decade. In the first case, the total number of new links increases as a linear function of the network size (the total number of nodes), while in the second case—similarly to the Internet and the World Wide Web—the growth of the network is "accelerated".

In both cases, the number of M&A events has been steadily high, culminating with a few mega-mergers in the last few years (see Pammolli and Riccaboni, 2002; Rivlin, 2000; Mergerstat, 2001).[2]

Data used for this study are drawn from the Collaborative Agreements Database (CAD) at the University of Siena. An important feature of CAD is that it provides information on typology, technological content, and date of signing for 23,473 collaborative agreements (10,036 LS, 13,437 ICT) and 2959 (714 LS, 2245 ICT) M&As, involving 12,483 (3915 LS, 8568 ICT) firms worldwide.

For each firm, we have collected additional information on location, size, main areas of activity, age, personnel and type. For each contract, CAD records detailed transaction-specific attributes such as date of signing, stage of development, technological content, targeted markets, and typology (viz. license, joint venture, co-development, etc.). In addition, for each collaborative agreement we distinguish one project *originator* (licensor-payee) from one or more *developers* (licensees-payers).

We begin our investigation by looking at total connectivity distributions in the two domains. In Fig. 1, the total connectivity density distribution for both LS and ICT are plotted on a double-log scale. The upper tails of both distributions are well fitted by a power law with exponent $\gamma = 2 \pm 0.1$. Fig. 1 reveals, however, the existence of a remarkable concavity, which substantiates rather significant departures from the theoretical power law distribution. As it is evident, the concavity is particularly pronounced in the case of LS.

In order to investigate the mechanisms behind the observed departures, we sort firms in decreasing order of connectivity and plot the Pareto rank–connectivity distributions on log–log scale. The results are shown in Figs. 2 and 3.

As noticed above, a first economic mechanism that can, in principle, sway the degree distribution from Pareto is the process of consolidation. Fig. 2 compares the actual distributions after tie-up events with the "merger-free" connectivity distributions. Since M&A events concentrate in 1998–2000 and merged companies usually remain separated de facto for long, we are allowed to evaluate the degree distributions of "mergerless" companies as if they never collapse into they relative *holdings*.

The comparison of distributions in Fig. 2 reveals that M&As do not significantly impact on the curvature of the Pareto rank–connectivity distribution (straight line on a double-log scale). Obviously, post-merger network concentration is higher in both sectors as the slope of the post-merger distribution is steeper than the slope of the "mergerless" distribution

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[2] *Life sciences*: 1996: Ciba-Geigy–Sandoz (*Novartis*); 1997: Roche–Boehringer Mannheim; 1998: Hoechst Marion Roussel–Rhône-Poulenc Rorer (*Aventis*); Sanofi–Syntélabo; Astra–Zeneca (*AstraZeneca*); 1999: Pharmacia & Upjohn–Monsanto (Pharmacia Corp.); 2000: Glaxo Wellcome–SmithKline Beecham (*Glaxo SmithKline*); Warner Lambert–Pfizer. *Information and communication technologies*: 1997: AOL–Computerserve; 1998: WorldCom–MCI; AT&T–Tele-Communications Inc.; AOL–Netscape Communications; Disney–Infoseek (43%); 1999: Lucent Technologies–Ascend Communications; 2000: AOL–Time Warner, France Telecom–Vodafone Airtouch (Orange); Alcatel–Newbridge Networks.

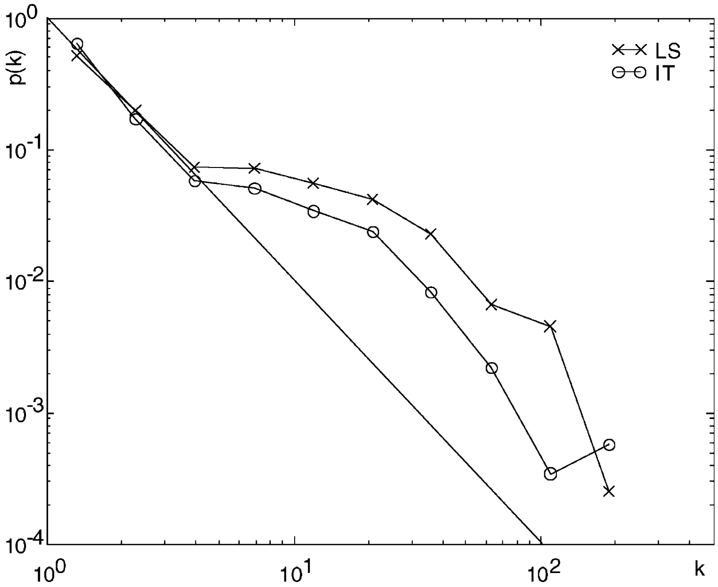


Fig. 1. Connectivity density distribution: LS and ICT.

(see also the OLS estimates in Table 1). However, the concavity of the distribution does not seem to be appreciably modified by M&As. Quite surprisingly, in LS the concavity of the post-merger connectivity distribution is lower than the correspondent "mergerless" distribution. The probability of a firm of being absorbed by mergers and acquisitions comes out to be essentially independent from connectivity. In both sectors, the acquisition of start-ups by established companies to capture new technological opportunities is counterbalanced by acquisitions of highly interconnected firms by late-comers, as well as by consolidation in downstream industries (pharmaceuticals and telecommunications).

Table 1
Pareto regressions

	log A	β	λ	R^2
LS				
Actual, linear	2.703	−0.614	–	0.92
Actual, cubic	2.703	−0.358	−0.116	0.98
Mergerless, linear	2.299	−0.443	–	0.83
Mergerless, cubic	2.299	−0.096	−0.156	0.98
ICT				
Actual, linear	2.436	−0.493		0.90
Actual, cubic	2.436	−0.247	−0.107	0.98
Mergerless, linear	2.398	−0.522		0.94
Mergerless, cubic	2.398	−0.366	−0.066	0.97
LS				
Developers, linear	2.276	−0.5214	–	0.84
Developers, cubic	2.276	−0.1323	−0.1941	0.99
Originators, linear	1.806	−0.3482	–	0.77
Originators, cubic	1.806	−0.0263	−0.1704	0.98
ICT				
Developers, linear	2.155	−0.5196		0.95
Developers, cubic	2.155	−0.3849	−0.0599	0.98
Originators, linear	2.029	−0.4832		0.93
Originators, cubic	2.029	−0.2876	−0.0880	0.99

A network can be represented as an ordered triple ($N(G)$, $E(G)$, f_G) consisting of a finite non-empty set of firms (N), a finite (disjoint) set of collaborations (E) and an incidence function f_G which relates an ordered pair of firms (originator–developer) with each edge. So far, we have compared LS and ICT networks in terms of size (N and E), firms connectivity (number of collaborations) and networks centralization (total connectivity distributions). In Fig. 3, we distinguish the relational roles of originators and developers, capturing the existence of major structural differences between the two sectors. In LS, the Pareto rank–connectivity distributions of merger-free firms as originators is markedly different from the correspondent distribution as developers. Developers' distribution is steeper than the originators' curve. On the contrary, in ICT, originators and developers

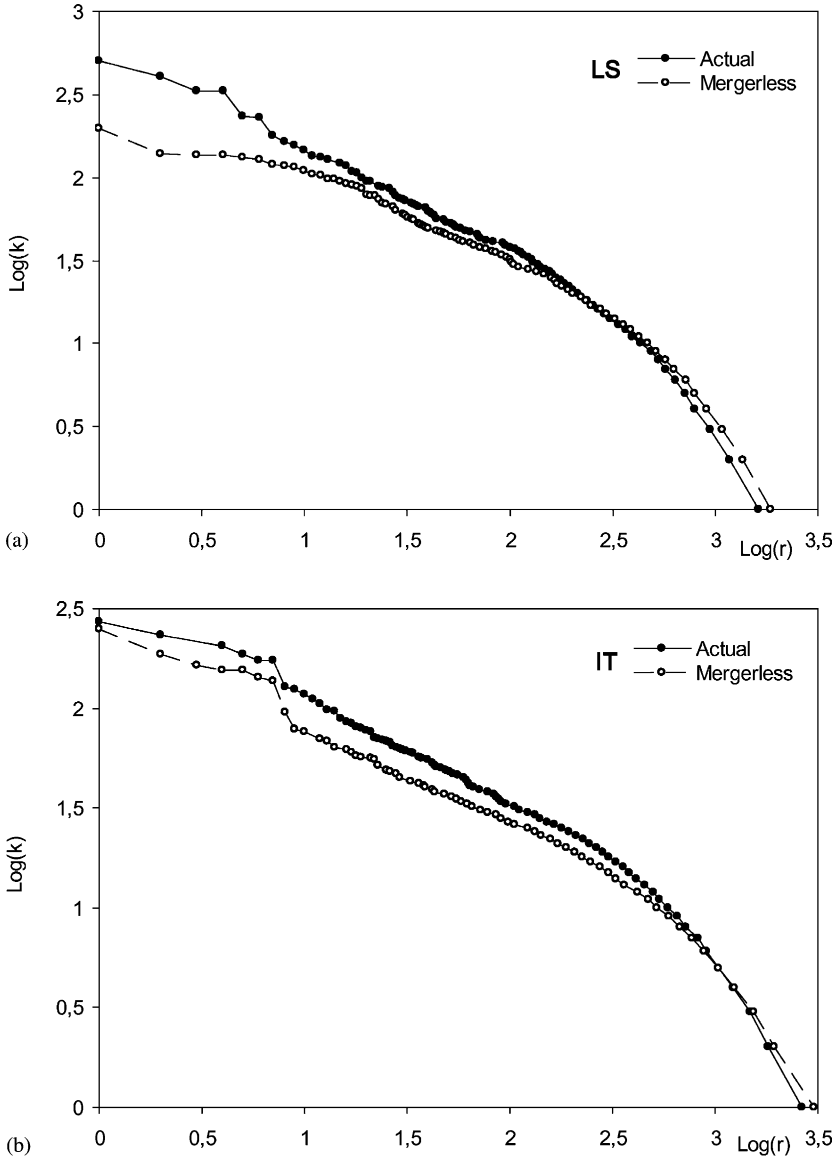


Fig. 2. Pareto rank–connectivity distributions: the effect of M&As in LS (a) and ICT (b) networks.

distributions are almost indistinguishable and close to the Pareto benchmark. Notably, LS "mergerless" distributions highlights again evident departures from Pareto. These findings are suggestive of different relational behaviors for the two types of firms in the two sectors, which cannot be attributed to M&As. Consolidation is only one of the possible explanatory variables for the observed departures from Pareto. Autocorrelation of growth opportunities has been identified as another possible mechanism leading to concavity (see Ijiri and Simon, 1977).

In order to assess the effect of this second component, we now focus our attention to the deal-making activity of "merger-free" originators and developers. Fig. 4 shows the probability of subscribing a new deal after any given time step from previous collaborations.

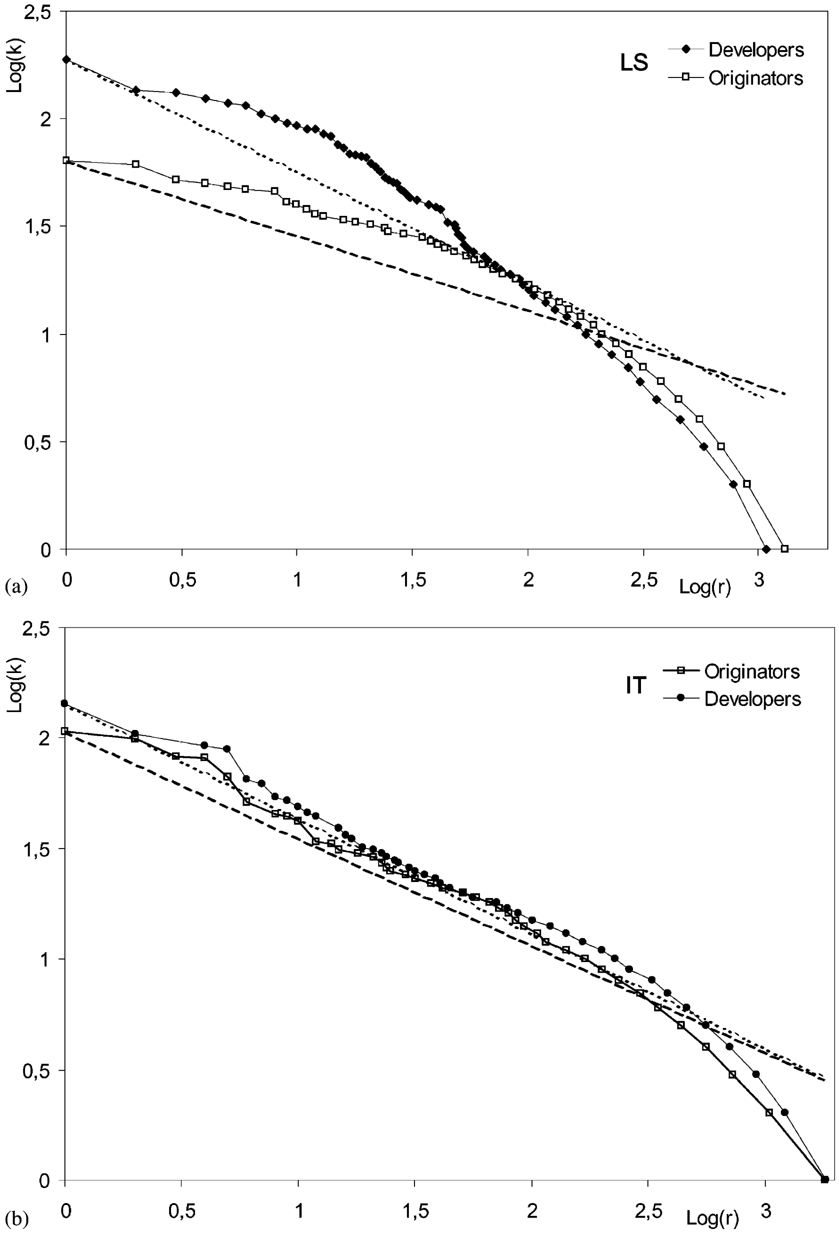
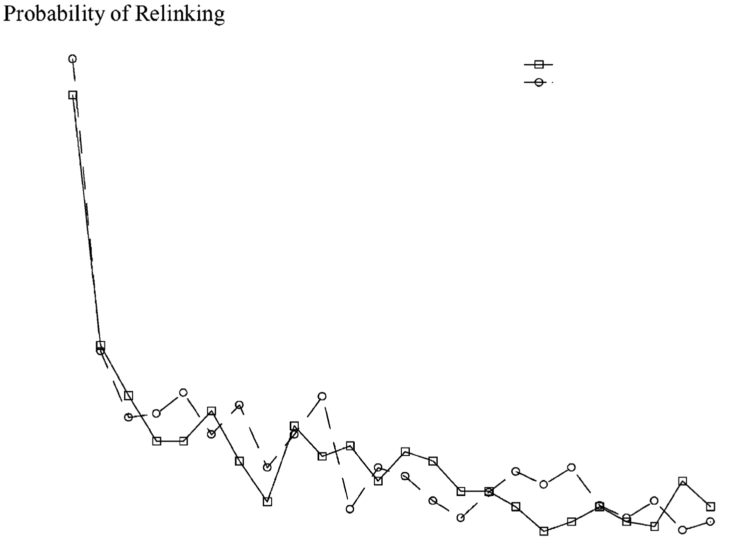


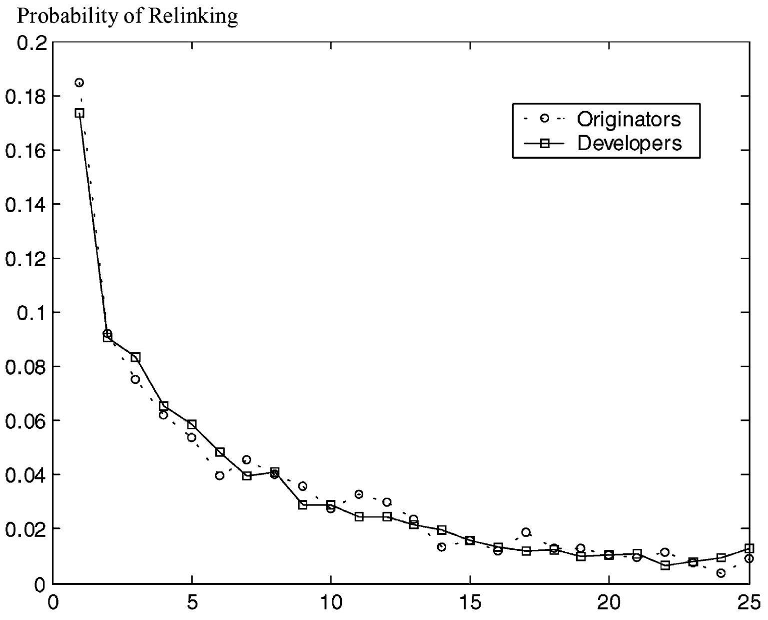
Fig. 3. Pareto rank–connectivity distributions of firms in the network of collaborative agreements: LS (a) vs. ICT (b), originators and developers.

Despite differences in the frequency of interaction, the probability of relinking decays exponentially for originators and developers in both networks. As the two networks are driven by an intense flow of entry, central firms ought to keep the pace with rapid technological advances constantly interacting with new comers.

The above results are confirmed in Table 1, in which we perform an OLS estimate of the theoretical Pareto distribution: $\log k = \log A + \beta \log r + \varepsilon$.



(a) Time (months)



(b) Time (months)

Fig. 4. Probability of relinking at different time steps: LS (a) and ICT (b).

The connectivity of each firm (k) and its rank (r) are shown to be linearly related on a double-log scale. Table 1 reports the values of the intercepts ($\log A$, i.e. the logarithm of the largest firm' connectivity) and the estimated slope coefficients (β). Moreover, in order to measure the extent of the concavity we have added a cubic term, then comparing the estimated coefficients (λ). As mentioned above, developers rank–connectivity distribution in LS highlights the highest level of concentration (β) and concavity (λ). While the first effect has to do with the process of consolidation, the pronounced departure from Pareto of the LS connectivity distributions cannot be explained, neither based on M&As nor on autocorrelated growth.

In order to improve our understanding of patterns of firm growth in the LS network, we introduce a simple simulative model based on two parameters that make possible a better characterization of the processes of growth for originators and developers (see Riccaboni, 2000).

The model is based on the simple assumptions of entry and proportional growth. A parameter (p) sets the interdependence between the growth of the network and the flows of firm entry. A parameter (q) gives the probability of having a cumulative relational regime, reflecting the relative growth of number of nodes versus number of links. Each simulation starts with N isolated nodes (firms).

At each time step, with probability p, a new originator enters the network, whilst with probability $(1-p)$ a link is originated by an already active firm. With probability q, an originator links to a developer chosen preferentially, in proportion to its connectivity. In this case, a new link is drawn from an originator to a developer, which is selected with probability $\Pi(d)$ proportional to its degree $k(d)$. Based on the evidence discussed in Powell et al. (1996), as well as in Orsenigo et al. (2001), we model $\Pi(d)$ as a linear function of $k(d)$. With probability $(1-q)$, an originator establishes a new link with a preexisting developer chosen at random.

We have tested different versions of the simulative model for different combinations of p and q. In a nutshell, two different generative processes turn out to be in place for originators and developers in LS. As for originators, the real-world connectivity distribution is accounted for by a regime of preferential attachment and sustained entry.

On the contrary, in the case of developers, the simulative model that better approximates the real-world distribution is a mixture of a random and a cumulative generative processes, with sustained entry.[3] The presence of a dumping factor of the preferential attachment mechanism of growth can lead to departure from Pareto in the rank–connectivity distribution in LS, reflecting specialization an division of labor. In LS, "popularity" effects are associated with reputation in a given relational role (originator versus developer). On the contrary, the ICT network is characterized by the presence of highly connected firms which act as network integrators and establish new links both as originators and developers. These differences are evident by comparing joint connectivity probability distributions (Fig. 5). While Fig. 1 shows the probability of having k connections—$p(k)$—Fig. 5 distinguish between the probability of having k_o collaborations as originators and k_d collaborations as developers—$p(k_\mathrm{o}, k_\mathrm{d})$—with $k_\mathrm{o} + k_\mathrm{d} = k$.

Let us suppose that the probability of subscribing a new deal depends only on k, while the role of each firm in the new deal (originator versus developer) is assigned by tossing a coin. In that case, joint distributions $p(k_\mathrm{o}, k_\mathrm{d})$ in Fig. 5 would correspond to the 3D analogous of Pareto distributions. Instead of having a straight line in double-log scale, the Pareto distribution can be represented as a symmetric pyramid in triple-log scale with respect to the main diagonal ($k_\mathrm{o} = k_\mathrm{d}$). In ICT (LS), $p(k_\mathrm{o})$ and $p(k_\mathrm{d})$ are positively (negatively) related. Fig. 5a and b show the joint connectivity distributions for LS and ICT, respectively. The two distributions are directly comparable, as they are plotted by k_o and k_d deciles on triple-log scale, and the integral of the curves is (approximately) equal to 1 in both cases. As it is evident, connectivity distributions in LS and ICT are characterized by opposite departures from the theoretical Pareto benchmark. In LS, firms tend to specialize in their relational roles and the probability mass is largely distributed toward the extremes ($k_\mathrm{o} = 10$, $k_\mathrm{d} = 0$ and $k_\mathrm{o} = 0$, $k_\mathrm{d} = 10$). On the contrary, the ICT distribution collapses on the main diagonal, revealing a higher incidence of firms which play both relational roles.

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[3] The Kolmogorov–Smirnov statistics are significant (10%) for high levels of p ($0.6 < p < .8$) and low levels of q ($0.1 < q < 0.5$), respectively.

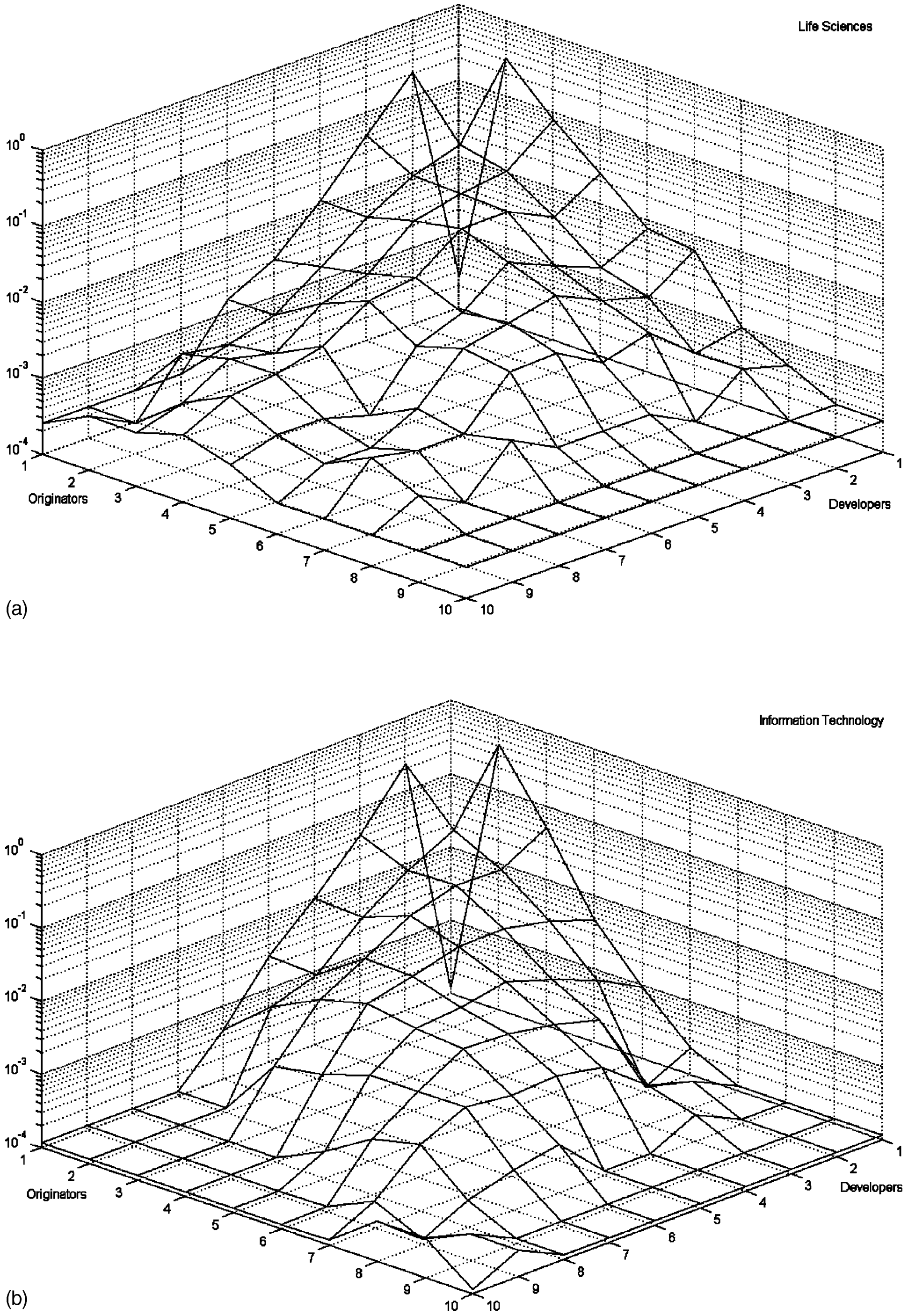

Fig. 5. Joint degree distributions as originators and developers, triple-log scale: LS (a) and ICT (b).

These results are suggestive of deeper structural differences between the two networks, which we aim at investigating in our future work, exploring the role played by different technological and market regimes.

4. Concluding discussion

In this paper, we have shown how an extension of stochastic explanations of internal firm size and growth fits a whole range of empirical findings. The scale-free structures that are in place in the two industrial networks that we have investigated can be considered as the outcome of a fairly general 'popularity is attractive' principle, which seems to sustain also the growth of systems of division of labor and of firms acting in them.

Being very general, mechanisms sustaining external growth in networks do not seem to differ from the ones that sustain firm internal growth. This result is suggestive of the existence of organizational principles that are general in nature, and map on both the internal structure of firms and the structure of markets and networks.

Moreover, we have shown how the dual nature of networks can convey information on topological properties of industries and roles/positions of firms within them (to begin with, the distinction between originators and developers), which can be used to understand some fundamental structures, mechanisms, and generative processes behind the growth of firms and industries, in the direction of building parsimonious and, at the same time, realistic, representations.

At present, our analysis has some obvious limitations. First, apart from information on firms' age and on the distinction between originators and developers, we did not take into account any node-specific attribute. Second, we have considered links of size unity, without addressing the properties of weighted networks and interactions strength. Third, the relational propensities of different nodes stay unchanged in our model. Finally, we do not dwell on decay and exit processes with the exception of mergers and acquisitions.

These shortcomings notwithstanding, this paper provides a benchmark in the analysis of firm growth in networks. Despite its limitations, it gives a parsimonious and general framework to 'reverse engineering' and compare the growth of networks in different industries, as we attempt to make our models more realistic.

Some of the current limitations of our analysis could be overcome, in the future, based on a higher availability of data on real systems and, in particular, of detailed topological and economic information on real-world networks. While at present, such data are relatively rare, the increasing interest in industrial networks is leading to the development of suitable data sets, offering further guidance for modeling and interpreting the growth of these complex and important economic systems.

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