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REGULAR ARTICLE

Social networks and labour productivity in Europe: an empirical investigation

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Abstract This paper uses firm-level data recorded in the AMADEUS database to investigate the distribution of labour productivity in different European countries. We find that the upper tail of the empirical productivity distributions follows a decaying power-law, whose exponent α is obtained by a semi-parametric estimation technique recently developed by Clementi et al. [Physica A 370(1):49–53, 2006]. The emergence of "fat tails" in productivity distribution has already been detected in Di Matteo et al. [Eur Phys J B 47(3):459–466, 2005] and explained by means of a model of social network. Here we show that this model is tested on a broader sample of countries having different patterns of social network structure. These different social attitudes, measured using a social capital indicator, reflect in the power-law exponent estimates, verifying in this way the existence of linkages among firms' productivity performance and social network.

Keywords Labour productivity · Power-law distribution · Semi-parametric bootstrap approach · Social networks · Social capital

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1 Introduction

A consistent flow of research on firms' and workers' productivity regarding the topic of technology innovation and diffusion has focused on generation and transmission of innovations through networks of firms (Pittaway et al. 2004), or on the relationship among social capital and productivity performance (Cohen and Prusak 2001).[1] As highlighted in Di Matteo et al. (2005), firms' network plays a decisive role in the imitation process of the innovative firms through which, according to the evolutionary literature perspective, innovations originally conceived by a given firm *percolate* outside it by imitation from other firms. In this way the innovation flows through the network of contacts and communications between firms. The significance of the underlying connection network comes into sight when the collective dynamics of the system is considered. As showed in several studies, above a certain threshold of complexity, natural, artificial, and social systems are typically characterised by networks with power-law degree distribution, i.e. "scale-free" networks (see, e.g. Albert and Barabási 2002). In very recent times, network theory gained *momentum* in explaining firms' performance also from a technical perspective. The amazingly rapid progress that took place in information technologies since the mid of '90s accounts for a noteworthy proportion of productivity growth. Contemporarily, it also broadened the role of networks in determining firms' labour productivity performances. The conjunct use of information networks along supply or customer chains pushed toward a higher specialisation and improvement of skills in labour force and, in general, leaded to remarkable changes in the competencies needed within firms in order to maintain competitiveness on the market (Motohashi 2007).

In this paper we extend the analysis of the relationship among network and productivity in two directions. First, we exploit the link between social capital, social network and productivity distribution among firms. We do not limit our analysis to the firms' network (see, e.g. Ahuja 2000), but we *embed* it in the study of social network characteristics, treating therefore also the non-economic aspects that determine the social environment in which firms operate and interact. According to Granovetter (2005), the social network influences firms' productivity through different channels: the mutual acceptance and the prizing of technical skills inside the community of workers within a firm; the control exerted among colleagues, that determines the quality of the effort and, therefore, the efficiency of single workers in a way analogous to principal-agent models; the interpersonal ties, inside and outside the firms, enforced by repeated interaction, that lead to a level of trust that eases the interrelations and the flow of information.

The second aspect of novelty consists in the method of analysis. Indeed, the impact of social network structure on productivity is quantitatively evaluated by means of labour productivity distribution features, in order to verify whether and to which extent

[1] See Rogers (2003) for a comprehensive topic review.

social systems and social capital favor the circulation of information and innovation through networks of firms. The differences recorded among firms' productivity levels within a country determine the shape of productivity distribution. As evidenced by Coleman (1988), stronger network ties make the circulation of information faster and less expensive. This, in turn, may reduce the gap in performances across firms by favoring the transmission of knowledge and innovations, and thus leading to a more even distribution of productivity among firms. Therefore, in this paper we investigate how differences in social capital reflect into disparities in productivity distribution shapes and parameters.

The study proceeds as follows: in Sect. 2, it is examined whether labour productivity follows a power-law distribution in a sample of 9 European countries. This assessment is of particular interest, since the sample of countries in object is not homogeneous from both an economic and a social point of view. The presence of power-law tails in such different contexts might reveal that this emergence does not depend on a particular underlying social structure, but it is consistent over different systems. The estimates of the power-law exponent are here obtained by means of the technique introduced by Clementi et al. (2006). This method adopts a subsample semi-parametric bootstrap algorithm for optimally selecting the number of extreme quantiles to be used in the upper tail estimation, and thus ending up with less ambiguous estimates of the exponent α. Furthermore, we model the network of firms along the lines of Di Matteo et al. (2005, but see also Di Matteo et al. 2004): the use of this model allows to get a quantitative measure of the role of the underlying network of firms in determining the shape of productivity distribution. According to this work, the emergence of "fat-tailed" distributions may be interpreted as the outcome of an analogous structure of the network, which must show slow decaying tails in its degree distribution, and, therefore, a "scale-free" type behaviour.[2] In Sect. 3, the link between networks of firms and social networks is illustrated by comparing the tail exponents of the labour productivity distributions to a social capital indicator by country, and also testing if social capital influences the aggregate growth of productivity. Finally, Sect. 4 summarizes and concludes.

2 Power-law decay in productivity distribution

Our aim here is to perform tail parameter estimations on labour productivity data through a recently developed method. The labour productivity is defined as added value over the amount of employees (where added value, defined according to standard balance sheet reporting, is the difference between total revenue and cost of inputs excluding the cost of labour). The results are used in the remainder of this section to link our empirical findings to a model of firms' interaction across a complex network.

[2] Pammolli and Riccaboni (2001) sustain this interpretation by detecting power-law distributions in firms' networks.

Table 1 The number of companies from 1996 to 2005 on AMADEUS database (Bureau Van Dijk) in the following countries and geographical sub-areas: Belgium (BEL), Finland (FIN), France (FRA), Germany (GER), East Germany (EASTGER), West Germany (WESTGER), Italy (ITA), North Italy (NORTHITA), South Italy (SOUTHITA), Netherlands (NET), Spain (SPA), Sweden (SWE) and the United Kingdom (UK)

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
BEL	4,205	4,396	4,733	5,076	5,378	5,698	6,104	6,240	6,258	1,314
FIN	981	1,432	1,416	1,752	1,901	2,030	2,283	2,470	2,451	1,255
FRA	9,239	10,745	12,450	13,045	13,570	14,204	15,468	15,911	17,855	3,037
GER	1,453	1,497	1,656	1,661	1,961	2,126	3,807	4,404	4,278	751
EASTGER	186	192	233	246	274	269	512	583	599	107
WESTGER	1,267	1,305	1,423	1,415	1,687	1,857	3,295	3,821	3,679	644
ITA	10,904	11,861	12,087	13,742	14,360	14,995	16,492	13,574	16,715	3,586
NORTHITA	7,945	8,604	8,845	9,956	10,312	10,682	11,834	10,292	12,037	3,011
SOUTHITA	2,949	3,257	3,242	3,786	4,048	4,313	4,658	3,282	4,678	575
NET	1,404	1,643	1,884	2,685	2,616	3,221	3,961	4,112	3,825	807
SPA	6,551	7,382	8,356	9,020	10,123	11,378	12,472	12,736	12,300	228
SWE	NA	2,437	3,674	5,815	6,387	6,855	7,278	7,517	7,728	2,768
UK	4,205	10,563	11,578	12,545	13,679	15,082	16,482	17,342	17,687	5,996

NA data not available

2.1 Data and methodology

In this paper we have used the AMADEUS database, compiled by Bureau van Dijk Electronic Publishing.[3] This data source contains firm-level data from all over Europe, and is available in different sizes. Firms in this study are taken from the "TOP 250,000 Module", including companies that fulfill one of three criteria regarding the magnitude of operating revenues, total assets and the number of employees.[4] The analysis is based on 10 years of data (1996–2005) for 9 countries (Belgium, Finland, France, Germany, Italy, Netherlands, Spain, Sweden and the United Kingdom); for some of them (Germany and Italy) we have also used data by geographical sub-areas (East/West Germany and North/South Italy, respectively). The number of observations for each year and country is shown in Table 1. It should be noted that the number of companies for all countries is lower in 1996 and 2005 compared to all other years in the time span. Therefore, results from these years should be used with caution, since they might not be completely reliable.

From these data we have calculated the empirical complementary cumulative distributions ($P_{\geq}(x)$, being the probability to find a firm with productivity larger than or equal to x), which show a very clear linear trend for large values of x in a log-log scale, implying a non-Gaussian character with the probability for large productivities

[3] Further details on the database can be found on the provider website: http://www.bvdep.com/en/amadeus.html.

[4] For France, Germany, Italy, Russia, Spain, the United Kingdom and Ukraine, the inclusion thresholds are €15 million in operating revenues, €30 million in assets and 200 employees. For all the other countries, they are €10 million in operating revenues, €20 million in assets and 150 employees.

well described by a power-law behaviour, i.e. $P_{\geq}(x) \sim x^{-\alpha}$. To extract the value of α we have used Clementi et al.'s (2006) subsample semi-parametric bootstrap algorithm for *data-driven* selection of the number of observations located in the tail of the distribution. This technique relies on the popular Hill's (1975) maximum likelihood estimator for the tail index α, given by

$$\alpha_n = \left\{ \frac{1}{m} \sum_{i=1}^{m} \left[\log x_{(n-i+1)} - \log x_{(n-m)} \right] \right\}^{-1}, \tag{1}$$

where n is the sample size, m the number of observations in the tail of the distribution and the sample elements are put in descending order, i.e. $x_{(n)} \geq x_{(n-1)} \geq \cdots \geq x_{(n-m)} \geq \cdots \geq x_{(1)}$. As well known, the main problem connected with the Hill's estimator is the decision about an appropriate tail size, i.e. the optimal number of observations m included in the calculation of α_n. This choice is accomplished by the authors through minimisation of the finite-sample mean squared error (MSE) of the estimator (1), so that an optimal m is defined by

$$m^* = \arg\min_m E\left[\left(\alpha^{\#}_{n_1} - \alpha_n \right)^2 \right],$$

where α_n is an initial estimate from the original sample and $\alpha^{\#}_{n_1}$ is the estimate obtained using the bootstrapped datasets drawn from a smoothed parametric distribution of $n_1 \leq n$ observations belonging to the null hypothesis of a complete sequence of goodness-of-fit tests for Pareto-type tail behaviour. The number of bootstrap replications is automatically chosen according to a three-steps procedure to achieve the desired level of accuracy, where accuracy is measured by the percentage deviation of the estimate obtained by running a finite number of bootstrap repetitions from the corresponding ideal bootstrap quantity estimated with an infinite number of resamples (Andrews and Buchinsky 2000). Since MSE comprises the variance and bias of the estimator, the optimal estimate α^*_n—making use of m^* observations lying in the tail—will be in this way a balance between the former (which usually decreases with increasing tail size) and the latter (which tends to increase with tail size).[5]

The point estimates of the tail exponent obtained by applying the semi-parametric technique can be seen in Table 2. Inspection of the results reveals slight differences among years and countries: for example, for some countries (Belgium, West Germany, Sweden and the United Kingdom) we observe relatively homogeneous entries for the tail indices, while for other countries (Finland, France, East Germany and Spain) the estimate of α has a tendency to decrease in time; exceptions to these temporal patterns

[5] Hill himself devised a data-analytic method for choosing m^* which is based on sequentially testing appropriate functions of the observations for exponentiality. However, the application of this procedure to our productivity data resulted in overestimation of the tail exponent compared to the semi-parametric bootstrap algorithm. This appears to empirically support Hall and Welsh's (1985) argument of a very gradual deterioration of the exponential approximation, leading Hill's method to largely overestimate m (and thus α by Eq. (1)).

Table 2 Estimates of the power-law tail exponent α by subsample semi-parametric resampling and 95% confidence intervals

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
BEL	0.99 ± 0.06	0.97 ± 0.06	0.93 ± 0.06	0.93 ± 0.06	0.86 ± 0.06	0.95 ± 0.06	0.97 ± 0.07	0.89 ± 0.06	0.91 ± 0.06	0.92 ± 0.11
FIN	1.25 ± 0.28	1.45 ± 0.19	1.49 ± 0.16	1.40 ± 0.16	1.21 ± 0.12	1.26 ± 0.12	0.94 ± 0.16	0.99 ± 0.12	0.99 ± 0.19	0.83 ± 0.15
FRA	0.92 ± 0.10	1.02 ± 0.11	0.76 ± 0.07	0.85 ± 0.07	0.73 ± 0.05	0.69 ± 0.04	0.66 ± 0.03	0.64 ± 0.03	0.74 ± 0.05	0.55 ± 0.08
GER	1.53 ± 0.13	1.44 ± 0.09	1.59 ± 0.09	1.48 ± 0.09	1.45 ± 0.11	1.41 ± 0.10	1.05 ± 0.18	0.94 ± 0.13	1.43 ± 0.08	1.30 ± 0.22
EASTGER	1.44 ± 0.16	1.33 ± 0.22	1.34 ± 0.20	1.30 ± 0.19	1.15 ± 0.16	1.45 ± 0.25	1.28 ± 0.14	1.15 ± 0.11	1.19 ± 0.14	0.86 ± 0.17
WESTGER	1.38 ± 0.15	1.40 ± 0.09	1.52 ± 0.14	1.46 ± 0.10	1.36 ± 0.11	1.40 ± 0.12	1.35 ± 0.10	1.16 ± 0.12	1.35 ± 0.11	1.21 ± 0.26
ITA	1.43 ± 0.15	1.47 ± 0.17	1.42 ± 0.10	1.34 ± 0.08	1.02 ± 0.06	1.13 ± 0.09	0.87 ± 0.06	1.16 ± 0.08	1.04 ± 0.07	1.09 ± 0.09
NORTHITA	1.37 ± 0.23	1.38 ± 0.23	1.49 ± 0.13	1.31 ± 0.09	0.96 ± 0.07	1.19 ± 0.12	0.83 ± 0.07	1.38 ± 0.09	1.12 ± 0.07	1.11 ± 0.10
SOUTHITA	1.13 ± 0.17	1.84 ± 0.10	1.83 ± 0.10	1.58 ± 0.08	1.16 ± 0.10	1.10 ± 0.13	0.99 ± 0.10	1.17 ± 0.09	1.06 ± 0.09	1.07 ± 0.17
NET	1.58 ± 0.18	1.38 ± 0.15	1.61 ± 0.14	0.83 ± 0.14	0.97 ± 0.11	0.64 ± 0.06	0.62 ± 0.06	0.65 ± 0.06	0.99 ± 0.08	0.96 ± 0.15
SPA	1.10 ± 0.10	1.19 ± 0.09	1.17 ± 0.07	1.04 ± 0.06	0.97 ± 0.05	0.90 ± 0.04	0.85 ± 0.04	0.78 ± 0.03	0.74 ± 0.03	0.98 ± 0.27
SWE	NA	1.17 ± 0.08	0.98 ± 0.05	1.05 ± 0.06	0.97 ± 0.06	1.00 ± 0.07	1.05 ± 0.07	1.04 ± 0.05	0.97 ± 0.05	1.12 ± 0.08
UK	0.99 ± 0.07	0.97 ± 0.07	0.93 ± 0.07	0.96 ± 0.07	0.93 ± 0.07	0.96 ± 0.05	0.97 ± 0.05	0.96 ± 0.05	0.93 ± 0.05	0.94 ± 0.07

The data used are taken from the AMADEUS database by Bureau Van Dijk, and the countries, years and sample sizes considered are those listed in Table 1. By exploiting the asymptotic distribution theory of the Hill's estimator, the 95% confidence intervals around the point estimates are given by $\alpha \pm f_{95\%} \frac{\alpha}{\sqrt{m}}$, where $f_{95\%}$ is the 95% point of the normal distribution are Germany, Italy, North and South Italy and Netherlands, for which the value of α shows a sharp decrease around the beginning of the current decade. However, the time interval under investigation is too short to decide whether these differences are due to major economic and/or political-institutional changes which could have led to a change of the extremal part of the distributions.[6]

2.2 Power-law-tailed distributions in firms' interaction networks

Di Matteo et al. (2005) have provided a simple model of technological change through a *social network* of interactions between firms to explain the occurrence of power-law tails in the empirically observed productivity distributions. The general idea behind this work is that a productivity-increasing technological innovation, originally introduced and adopted by a certain firm, can spread over time to other firms by imitation if they interact through a "scale-free" type network with degree distribution given by $p(k) \sim k^{-(\alpha+1)}$. The model predicts that the aggregate distribution for the productivity of the ensemble of firms is given by a normalised sum of Gaussians with averages distributed according with the connectivity in the network of interactions among firms. Therefore, it is the special structure of the underlying network, having slow decaying tails in its degree distribution, which shapes the aggregate productivity distribution. This theoretical prediction results in good quantitative agreement with the empirical results for the productivity distribution in France and Italy in the years 1996–2001 based on the "TOP 1.5 million Module" of AMADEUS database.[7]

Here we extend the analysis to actual empirical evidence coming from our dataset of firms fulfilling the "TOP 250,000 Module" inclusion criteria. Figures 1 and 2 show the log-log plot of the complementary cumulative distributions of labour productivity corresponding to the years 1996–2005 for two different countries: Belgium and the United Kingdom.[8] We find a quantitatively good agreement by considering an underlying scale-free network with degree distribution given by $p(k) \propto k^{-(\alpha+1)} \exp(-\beta/k)$, averages $k_l^{(1)} = m + z_l n$ directly proportional to the number of connections z_l that each firm l has in the network, and variance equal to σ. We note that, although there are several parameters to calibrate, the tail behaviour of the theoretical distribution is

[6] For a more in-depth investigation of the tail behaviour, we have also fitted our data to the α-stable distribution using the program STABLE (Nolan 1997, 1999a,b, 2001), available from JP Nolan's website: academic2.american.edu/~jpnolan. We noticed that only in a small number of cases the 95% confidence intervals of the semi-parametric tail index estimates extend to the realm of stable laws, and that in a more limited number of cases the tail index estimates calculated from the stable model are in a somewhat close accordance with the semi-parametric ones. But this is to be expected, since semi-parametric tail index estimation provides a tight fit of the distribution outer parts, whereas the stable law parameters are selected to approximate the entire shape of the empirical distribution (DuMouchel 1983, Lux 1996).

[7] In the "TOP 1.5 million Module", British, French, German, Italian, Russian, Spanish and Ukrainian companies are included if they satisfy at least one of the following criteria: operating revenues bigger than €1.5 million; total assets bigger than €3 million; number of employees bigger than 20. For all other countries, companies are included if their operation revenue is bigger than €1 million, or total assets are bigger than €2 million, or the number of employees is bigger than 15.

[8] Productivity data have been deflated by using the implicit GDP deflator (2000=100) taken from the OECD Statistics Portal (www.oecd.org/statistics/).

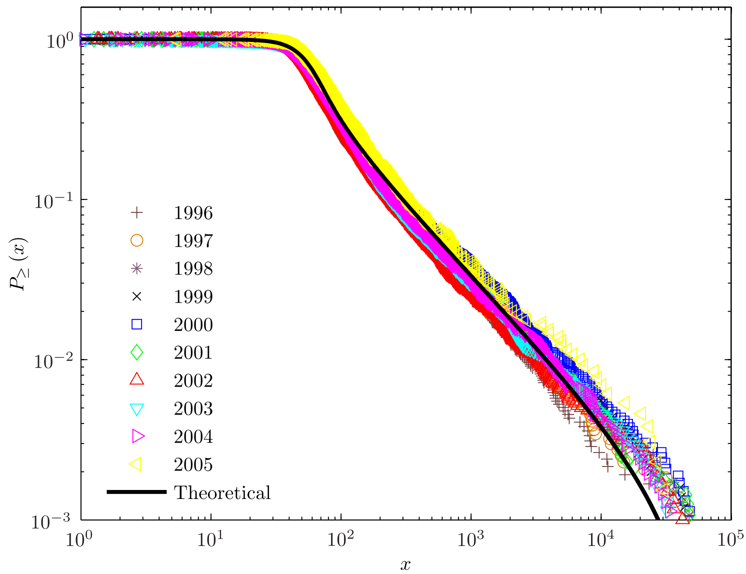

Fig. 1 Complementary cumulative distributions for the labour productivity in Belgium over the years 1996–2005. The theoretical behaviour (*black solid line*) is for $\alpha = 1.84$, $m = 33$, $n = 20$, $\sigma = 16$ and $\beta = 0.5$

controlled only by the power-law exponent α, while in the small and medium ranges the other parameters have a larger influence. From our analysis we observe that the theoretical curves (drawn as solid lines) fit well the empirical findings with $\alpha = 0.84$, $m = 33$, $n = 20$, $\sigma = 16$ and $\beta = 0.5$ for Belgium, and $\alpha = 0.88$, $m = 24$, $n = 11$, $\sigma = 16$ and $\beta = 0.6$ for the United Kingdom. Very good levels of agreement (not shown here but available upon request) have also been obtained for the other countries considered in our study; the parameters used for the theoretical curves are shown in Table 3. Notice that, although there is still matching between the theoretical predictions and the empirical findings, the numerical values we need to theoretically approximate the shape of the East German empirical distributions in an appropriate way are somewhat different from those of the other countries. This might be due to the limited number of entries this geographical area accounts for over the entire period of investigation, which shapes the productivity distributions differently than the others, especially in their outer parts.

3 Social network, social capital and economic performance

A huge literature focuses on the relationship among *social capital* and productivity of economic units or organisations (see Cohen and Prusak 2001, among others). In particular, some authors (e.g. Fukuyama 2000) tend to put emphasis on qualitative aspects of the relationship network-capital, drawing the attention to the capability of social capital within developed societies of linking heterogeneous social networks and

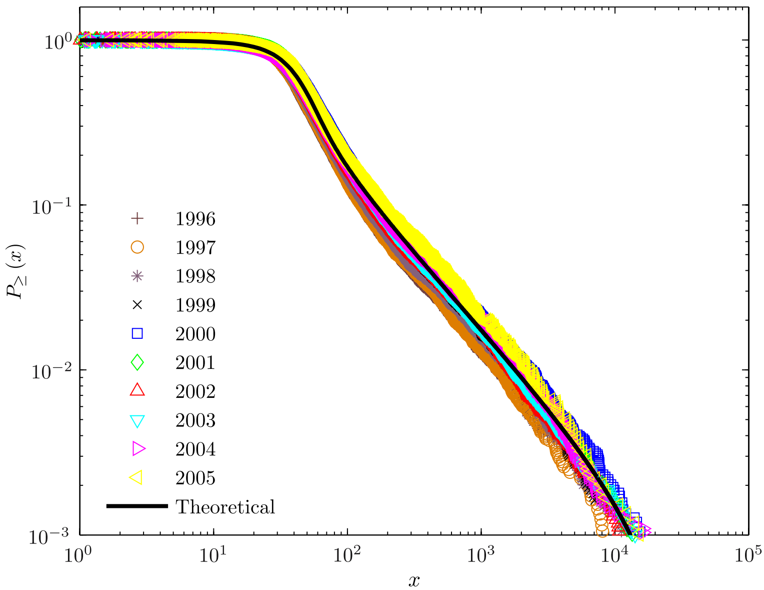

Fig. 2 Complementary cumulative distributions for the labour productivity in the United Kingdom over the years 1996–2005. The theoretical behaviour (*black solid line*) is for $\alpha = 1.88$, $m = 24$, $n = 11$, $\sigma = 16$ and $\beta = 0.6$

improving communication and information flows. Along these lines, our aim here is to investigate whether social capital plays a role in the transfer of knowledge, information, and technology through the social network of firms in a country (on this point see in particular Ahuja 2000). The basic hypothesis is that a higher level of social capital improves the efficacy of social network linkages, favoring and strengthening connections among agents, and lowering costs and time of communication (Coleman 1988). In terms of the present study, a more effective social network reduces the relative distances among firms' productivity levels, since innovation and technological information flow more rapidly and with lower costs (Granovetter 1985). Firms' productivity, therefore, results more evenly distributed, and the power-law exponents increase. The verification of this hypothesis introduces an original way to investigate the relation among social capital of a country and economic performance at aggregate level, since countries with different levels of social capital should display as well a different power-law exponent in labour productivity distribution.

By social capital we mean the 'features of social life-networks, norms, and trust, that enable participants to act together more effectively to pursue shared objectives' (Putnam 1995, pp. 664–665). This definition supports the choice of performing a country-level analysis, since a nation is supposed to represent a homogeneous sample as regards social network and institutional aspects. The concept of social capital was firstly introduced in sociology with reference to groups or communities. The extension of the concept at the country level, operated by political scientists, has been initially subject to critics, especially as regards measurement and distinction among human and social capital (Solow 1995). In more recent years, some of the cited studies performed

Table 3 Model parameters used to draw the theoretical curves for all countries and geographical sub-areas

	α	m	n	σ	β
BEL	0.8	33	20	16	0.5
FIN	1	30	14	12	0.5
FRA	0.7	30	10	12	0.3
GER	1	36	15	18	0.9
EASTGER	1.3	10	6	8	10
WESTGER	1.1	35	18	16	1
ITA	1.1	32	13	18	1.5
NORTHITA	1.2	28	19	16	1
SOUTHITA	1.1	23	19	16	1
NET	0.8	34	14	16	0.6
SPA	0.8	21	13	18	0.2
SWE	0.9	30	7	12	1.5
UK	0.9	24	11	16	0.6

at country (Coleman 1988) and sub-country level (e.g. Di Giacinto and Nuzzo 2006) demonstrated the usefulness of the concept of social capital, in particular for investigating social network features. Besides, Putnam (2000) stresses the relevance of social capital in improving the performance of individuals, since it puts them in a connected network. Indeed, social networks are often identified by specialised literature as the "structure" of social capital (e.g. Burt 2000), concept that is well specified by Bourdieu (1996, p. 249): "the volume of social capital possessed by a given agent [...] depends on the size of the network of connections that he can effectively mobilize". In order to obtain a synthetic indicator, empirical analyses usually adopt international surveys. Along the lines of most of these works, we employ the *World Values Survey* (*WVS*), a data source designed to enable a cross-national/cross-cultural comparison of values and norms in a wide variety of areas, and to monitor changes in values and attitudes in societies all over the world.[9] In particular, we refer to the latest available wave of the WVS by adopting as a social capital measure the *trust*, quantified by the percentage of interviewed people who agree to the assertion that "most people can be trusted".[10] According to Knack and Keefer (1997) and Sabatini (2006), among others, this quantity is likely to be deeply related with economic and productivity performances.[11] Moreover, the use of this proxy permits to avoid Portes' (1998) critic, according to which the isolation of social capital's definition from its effects would be ambiguous and, with particular reference to trust, could be reduced to the result of

[9] To date, the World Values Survey has carried out four waves (1981–1984, 1989–1993, 1994–1999, and 1999–2004) of national surveys representative of the values and beliefs in more than 80 countries on all six inhabited continents. The data are available for free download from the project website: http://www.worldvaluessurvey.org/.

[10] The exact question in the WVS is: "Generally speaking, would you say that most people can be trusted, or that you cannot be too careful in dealing with people?".

[11] In order to avoid biases due to the oversampling of certain categories of people interviewed, all the answers to these questions have been pondered by the weights provided in the survey itself.

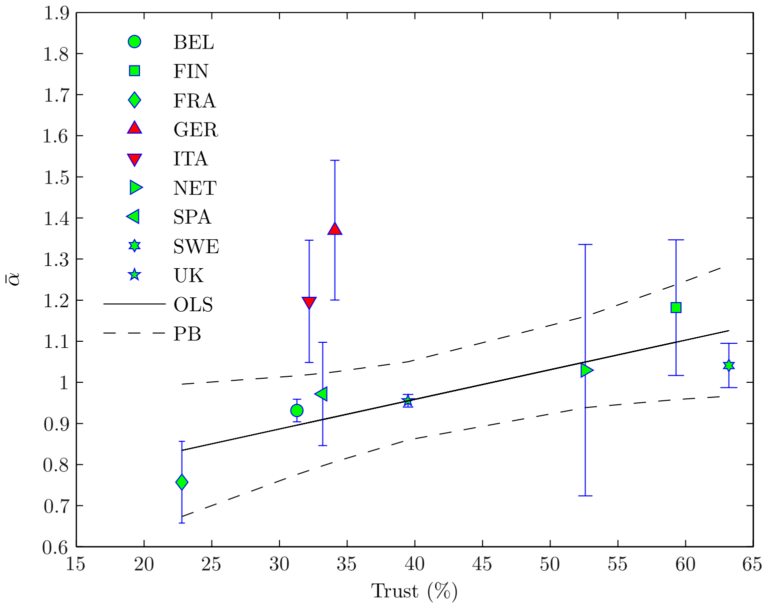

Fig. 3 Error bar plot of the average tail index estimate against the WVS-based trust measure. The length of each error bar equals two times the standard error of the mean. The *black solid line* is the ordinary least squares (*OLS*) fit to the data with 95% prediction bounds (*PB*)

the effectiveness of legal enforcement in a country's system (Guiso et al. 2004). This linkage among social capital and legal enforcement in the WVS is better captured by the variable *civic*, which concerns a series of social behaviours (such as "avoiding a fare on public transport") that can be never, partially or totally justified by the interviewed persons (see Knack and Keefer 1997, for a more detailed explanation and an investigation of the relationship among civic and trust). Nevertheless, the measure of interpersonal trust reported in the WVS appears to be consistent with its definition as an equilibrium outcome of a society where non-legal mechanisms force people to behave cooperatively (Coleman 1990).

On Fig. 3 we plot $\bar{\alpha}$, the average of the power-law exponent estimates for each country over the period under investigation, as a function of the level of trust; the corresponding values are shown in Table 4.[12] By observing the graph, one can notice that a tendency toward a positive trend seems to emerge between the average value of the estimates of power-law exponents and the level of trust. However, given the low number of cases included in the analysis, it is not possible to infer any further conclusions.

[12] Due to the reduced number of observations, which might bias the results for some countries, we exclude the tail index estimates for 2005 from the computation of the mean for countries with less than 1000 observations in that year (namely, Germany, West Germany, South Italy, Netherlands and Spain). As regards East Germany, the mean is computed considering all values, since anyway the number of observations is always less than 1000. Notice that the choice to use the average value of the estimates permits to smooth temporary variations (that in some countries,—e.g. Germany, Italy and Netherlands—are not negligible), and it is likely to be more appropriate to enable comparison with the wave of WVS data we use, since this data collection was undertaken in the central years of the period under analysis for firms.

Table 4 Temporal averages of the power-law exponent estimates ($\bar{\alpha}$) over the period under investigation and percentage level of trust (WVS, 1999–2004 wave) for each country and geographical sub-area considered in the study

	$\bar{\alpha}$	Trust (%)
BEL	0.93 ± 0.03	31.30
FRA	1.18 ± 0.17	59.30
FIN	0.76 ± 0.10	22.80
GER	1.37 ± 0.17[a]	34.10
EASTGER	1.29 ± 0.09	48.30
WESTGER	1.36 ± 0.08[a]	40.70
ITA	1.20 ± 0.15	32.20
NORTHITA	1.23 ± 0.17	NA
SOUTHITA	1.32 ± 0.26[a]	NA
NET	1.03 ± 0.31[a]	52.60
SPA	0.97 ± 0.13[a]	33.20
SWE	1.04 ± 0.05[b]	63.20
UK	0.96 ± 0.02	39.50

Also shown is the estimated standard error of the mean
[a] Excluding 2005
[b] Excluding 1996

Nonetheless, some deviations from this trend are present. In particular, the calculated value of the linear (Pearson's) correlation coefficient between these two variables is 0.28, with an estimated p-value for testing the hypothesis of no correlation equal to 0.46; however, once Germany and Italy have been excluded from the calculation, the estimated correlation coefficient and p-value are 0.86 and 0.01, respectively. These results are confirmed if one uses Kendall's τ and Spearman's ρ as more general and robust measures of dependence, obtaining $\tau = 0.39$ (p-value $= 0.18$) and $\rho = 0.47$ (p-value $= 0.21$) when the two countries are included in the analysis, and $\tau = 0.81$ (p-value $= 0.01$) and $\rho = 0.93$ (p-value $= 0.01$) when they are not. The positive but significant (at the 5% significance level) correlation only once Germany and Italy are excluded from the computation points to an *outlying* behaviour of these countries, which indeed reveal an average value of the power-law exponent significantly higher compared to the other countries. A possible explanation of this behaviour involves the particular heterogeneity within each country. The aggregates of these two countries are actually the sum of two different social networks and economic systems: East and West for Germany, North and South for Italy.[13] The average values of the tail index estimations for the above-mentioned levels of geographical disaggregation is shown in the second column of Table 4. As regards Germany, the value of trust is somewhat bigger in the Eastern part (48.3% against 40.7% of the West), but it should be noted that at the beginning of the period under observation for firms the percentages of trust were 24.3 for the East and 39.9 for the West, respectively (1997 WVS data).[14] During this time, firms in East Germany were catching up Western ones: the aggregate labour productivity of East Germany (as a percentage of the West Germany's level) progresses

[13] See Vecernik (2003) for Germany and Di Giacinto and Nuzzo (2006) for Italy.

[14] These results do not differ greatly from the values of immediate pre-unification period. Indeed, East and West Germany's 1990 WVS percent levels of trust equalled to 20.1 and 31.1, respectively.

from 45% in 1990 to approximatively 70% in 2002 (Uhlig 2006); simultaneously, the power-law exponent estimates of the Eastern firms' productivity distribution result lower at the end of the period of observation with respect to the beginning, while they remain substantially stable in West Germany.[15] If considered together, these matters suggest that the improvement in Eastern workers' productivity has been accompanied by a relevant integration of the different social networks and an increase of the differences between firms in the initially disadvantaged area. Therefore, a Schumpeterian mechanism seems to be at work here: not all firms took advantage from the new body of technologies and information available. In particular, the augmented level of social trust did not determine a generalised improvement in firms' productivity due to the massive migration of workers towards the West and, consequently, the difficulties for Eastern firms in hiring skilled workers. According to Cooper (1999),[16] this networking problem is at the root of the slowdown in the catching-up process observed after 2002. In other words, over a certain starting threshold of heterogeneity, even a remarkable improvement in social capital has limited or no effect on the network structure, the communication among weakly connected points being problematic (the "structural holes" proposed by Burt). As regards Italy, given the unavailability of geographical sub-area survey data, no definitive conclusions can be drawn from the disaggregation analysis, even though the average level of power-law exponent for Northern firms is slightly lower.

4 Conclusions

In this work we have detected the emergence of power-law tails in labour productivity distributions for nine European countries and different time periods. We have modeled the empirical labour productivity distributions with the model introduced by Di Matteo et al. (2005), and compared its outcomes with the empirical power-law exponents estimated by means of Clementi et al.'s (2006) algorithm. The model has been validated for all cases, confirming that power-law tails can emerge from scale-free contact-networks. Moreover, we have investigated the relationship between productivity distribution features and social trust, evidencing a tendency toward a positive relationship between the mean values of the power-law exponents of labour productivity and the level of trust. However, the data appear scattered and, because of the reduced number of points, it is not possible to draw a definitive conclusion.

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[15] A word of caution is needed here due to the low number of observations for East Germany.

[16] But see also Rosenfeld et al. (2004) on the related question of "clusterization" of Eastern firms.

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