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R&D cooperation within Italian technological districts: A microeconometric analysis*

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Abstract

The purpose of this paper is to investigate the determinants of inter-firm R&D collaborations in a particular type of innovation network, the technological districts created in Italy under a specific public policy to foster innovation and economic development at the local level. Using an original database containing information on the collaborative research projects activated by the districts, we find that the structural characteristics of the individual districts play an important role upon firms' collaboration choices: the probability of cooperating is higher in districts in which universities have a major weight and in districts with governance more oriented towards market logic. As regards the governance, the estimates also reveal a strong moderating effect on other important determinants of R&D cooperation, such as geographical proximity and absorptive capacity.

JEL Classification: L14, O31, O32

Keywords: R&D cooperation, innovation networks, firm behaviour, dyadic regession model

* The authors are solely responsible for the content of the paper. The views expressed are purely those of the authors and may not in any circumstances be regarded as stating an official position of the AGCOM

1. Introduction

In the last few decades, public policies to promote research and development (R&D) of several advanced countries have attached increasing emphasis on the formation of innovative networks, which are considered as an ideal context to foster knowledge creation and dissemination. In Italy, a particular state intervention has been implemented to create technological districts (TDs henceforth), that is innovative networks geographically concentrated in specific areas and in which various types of organisations (financial institutions, private and public research institutions, local authorities, private firms, etc.) carry out intense R&D activities. The *raison d'être* of such policy is the agglomeration of innovative firms and other institutions that can foster innovation, generating competitive advantages and economic development of local areas.

This paper sets out to use econometric analysis based on a sample of Italian TDs in order to identify the factors that promote cooperation among firms in the collaborative projects implemented by the various TDs. Then, our research contributes to the literature on the microeconomic choice to collaborate in R&D within innovative networks.

Our analysis differs from previous studies because it considers the strategies of collaboration within innovative networks that are characterized by two main peculiarities: *i)* their creation is conditioned on public funding and requires a decision-making process which starts from the *top*; *ii)* R&D activities implemented within them are managed according to a well-defined governance model; in this respect, the organisational and management structure may have an active role in the formation of partnerships for R&D activities. The existing literature, instead, appear chiefly centred on spontaneous collaborative relations between firms which are not driven and managed by external governance.

Such particular characteristics suggest the analysis should include not only the factors already identified in the literature as determinants of cooperation, but also the elements characterising individual districts. Thus, our research question concerns whether the drivers highlighted by the literature and/or the particular features of the districts are relevant in the context of Italian TDs to explain the formation of partnerships among firms.

Using a sample of collaborative research projects implemented in six TDs during the period 2005-2010, we estimate a logistic regression model for dyadic data. The results of our econometric analysis indicate that the structural characteristics of TDs play an important role in determining the propensity to cooperate. Estimates show that the presence of universities in a TD promotes collaborations among firms. Moreover, the management mode of a TD, in other words the type of governance, has a major impact: governance with a market oriented approach increases the propensity to cooperate. Further findings confirm the importance of network effects, as well as of

other factors indicated by the industrial organisation literature. In addition, we find that the governance of a TD plays a moderating effect on the relationship between the probability of cooperating and both geographical proximity and firms' absorptive capacity.
The paper is structured as follows: Section 2 provides a selected review of the theoretical and empirical background related to innovation networks. Section 3 describes the specific policy adopted in Italy to promote the creation of TDs. Section 4 presents the data and the econometric model, while Section 5 discusses the empirical results. Section 6 concludes the paper.

2. Theoretical and empirical background for technological districts

From a theoretical point of view, the modern innovation theory has emphasized that knowledge creation and dissemination is a localized process (Lundvall and Johnson, 1994; Storper, 1995). In line with this idea, the concept of regional innovation system (RIS) - introduced in the policy debate in the late 1990s as a regional interpretation of national innovation system (Cooke et al., 2004) - has attracted a growing importance in innovation policy. The RIS framework, defines innovation as a cumulative and non-linear process, resulting from formal and informal, voluntary and involuntary interactions between different local agents (such as firms, universities, research centers and local governments). According to this concept, the Triple Helix Model of innovation, which considers the close collaboration between University, Government and Industry as the essential engine of development for the local economy (Etzkowitz and Leydesdorff, 1995; Etzkowitz and Leydesdorff, 2000), is considered as the state of the art in the literature concerning regional innovation policies. It emphasizes that regional governments assume the key role of coordinator among different stakeholders involved in knowledge generating processes, because they have important competences and budgets in the field of innovation as well as a geographical proximity to local agents. Then, they can be considered as the most appropriate actors in order to align the interests of different local agents, fostering the creation of local innovation networks and the connectivity among different types of shareholders.
This model may be aptly combined with other approaches derived from the systemic view of the firm (Freeman, 1984; Golinelli, 2005), and with social network analysis (Granovetter, 1985; Burt, 1992; Gilsing, 2005) to highlight the positive effect of cooperation within innovative networks on technological progress and hence on the growth and competitiveness of local production systems.
Despite the extensive studies on technological clusters and regional innovation systems worldwide, empirical analyses of Italian technological districts are very scant. Patrucco (2003) using the case study of a TD in northern Italy shows that the number and heterogeneity of firm relationships positively impact on the innovation capabilities and growth of firms participating in the district.

Further contributions mainly evaluate the coherence between the economic specialization patterns of the Italian regions and the activity of the future district. To this end, some authors have sought to identify the key variables for suitable assessment of an area's technological potential. Lazzeroni (2010) identifies two methodological approaches: the first, starting from a large number of variables, uses multivariate analysis techniques (Bonavero, 1995; Miceli, 2010) or composite indicators such as the EU's European innovation scoreboard to measure the degree of local technological specialisation; with the second approach, variables are chosen a priori which might be representative of research potential in the areas in question (see, for example, Capuano and Del Monte, 2010). It is precisely this second approach, albeit more radical insofar as it is based on the construction of theoretical models, which would appear more suitable for analysis in local contexts where data are often unavailable. In this case, the factors deemed important are often identified through a comparison of existing situations, measuring the technological potential of various geographical areas also by means of qualitative variables (Monni and Spaventa, 2009). Lastly, a recent paper (Bertamino et al. 2016) sought to assess the economic performance of firms that participate in Italian technological districts. By using impact evaluation methods, the authors find that the performance of firms that joined a TD did not differ significantly from that of similar firms that did no. Similar results are shown by Liberati et al. (2015) on a sample of firms operating in science and technology parks: their business performance and propensity to innovate are not improved compared with external counterparts.

3. The public intervention for technological districts in Italy

As an instrument able to produce development and growth, TDs was first introduced into Italy with the Guidelines for Scientific and Technological Policy of the 2002 and then bolstered under the 2005 – 2007 national research programme (PNR). These planning documents stress the need to create, in certain areas of Italy, science parks in research and innovation able to promote collaboration between the various actors in the R&D production chain, drawing particular benefits from '*…public-private collaboration, supported by a process of institutional understanding between central, regional and local administration*'.[1] TDs receive public funds from European Union as well as central and local Italian governments; funds provided by the central government are prevalent.[2]

The area dimension of scientific research and technological development assumes a crucial role in such a policy: the creation of a TD in most cases requires a decision-making process which starts

[1] Italian Ministry of Education, University and Research (MIUR): National Research Programme 2005-2007, pp. 41.

[2] The Ministry of Education, University and Research (MIUR) estimates nearly in 500 million of euros the public resources distributed to the TDs until the end of 2011.

from the *top*. The initiative to establish TDs lies with the individual regions which have to present a project to the Italian MIUR so as to promote collaboration on specific innovative sectors between large, small and medium enterprises on the one hand, and public and private research institutes on the other. It is thus a matter of creating science parks for research and innovation. A prerequisite for the establishment of a TD is also identifying a geographical area that has substantial resources and technological skills that are consistent with the activity of the future district. The local variation in socio-economic structures in Italy has led to the creation of somewhat different TDs (Bossi *et al.*, 2006). However, we may identify a series of activities common to all TDs, namely: *i*) cooperation among the actors (networking), *ii*) local supply of high-level training, *iii*) support and assistance for start-ups through specialised finance, chiefly in the form of venture capital.

Starting from area technological specialisations (in many cases in areas at a sub-regional scale), such districts should be able to trigger a virtuous process between the world of research and industry that may lead to the development of high scientific skills of importance even at the international level.

Thus TDs are intended to combine the advantages of spatial agglomeration (closeness) of high-tech activities, typically knowledge spillovers, and creation of specialised labour and services, with the advantages of establishing networks, such as sharing the costs and risks associated with R&D. Moreover, thanks to the creation of collaboration networks it is also possible to incentivise SMEs, decoupling from the classic view that sees mainly large firms as the driver behind innovation and development processes.

Another fundamental criterion established by the government for setting up TDs is the creation *ad hoc* of a legally empowered governance authority to represent the TD and undertake the task of managing its activities according to a well-defined governance model.[3] The Articles of Associations of these authorities explicitly specify that the aim is to foster the development of the district as an integrated system of research and technological innovation. To that end governance authorities carry out "*all possible activities they deem necessary*", including the promotion of collaborative networks for the co-production and transfer of knowledge, according to the specific mission to manage and coordinate whole districts.

4. Data and econometric model

4.1 Sample description

[3] By governance authority or governance body we mean the legally established entity, created ad hoc, responsible for the management and coordination of the district and relative activities. It is usually a cooperative society or foundation whose members are also considered members of the district.

The empirical analysis considers six of the most important technological districts recognised by the MIUR. Most of the data were initially collected via the internet sites of the TDs and the Ministry. This information was subsequently verified and supplemented by interviews with those in charge of, or representing, the various districts. The availability of certified data and the degree of collaboration established with each district were essential elements for choosing the six TDs analysed herein. The sample in question, though only referring to some of the TDs operating in Italy (27 at the end of 2014), appears representative of the reference population both as regards the sectoral specialisation and with reference to geographical location: the districts considered belong to different technological sectors and to different regions, with a homogeneous split among the various areas of the country. Starting from the creation of various districts, mostly occurring in the two-year period 2005-2006, we collected data on research projects activated by the year 2010 using regional national or European public funds, in which the district governance authority played a leading and/or coordinating role. For each district, the information available concerns the projects undertaken during the period 2005-2010 and the participants. The amount of funds dedicated to such projects is around 100 million euros and is mostly provided by public sources.
In addition, the empirical analysis is based on two further sources of data: Bureau van Dijk for accounting variables of all companies participating in the TDs, whether domestic or foreign, and OECD for information on patent applications to the European Patent Office.

4.2 Dependent variable and econometric model

We measure R&D cooperation by the joint participations of firms in TD projects that are in the execution phase or already completed. For each district we constructed an actor-project matrix (affiliation matrix) containing the value 1 if the actor participated in the various research projects, and 0 otherwise; such a matrix, multiplied by its transpose (project-actor matrix), yields an actor-actor matrix (adjacency matrix) containing for each possible pairs of actors the number of collaborations in the research projects of the DT. Importantly, we consider each district as an individual network. Since only three firms (which we exclude from the sample) participated in more than one district and gave rise to cross-district collaborations, our choice seems appropriate.
The actor-actor matrix thereby created is thus a square symmetric matrix of dimension $n \times n$ whose elements on the main diagonal indicate the number of projects undertaken by each actor, and other elements indicate the collaboration links between each pair of actors. Given that more than 98% of pairs has 0 or 1 collaboration, we create a dependent variable equal to 0 for pairs with no collaborations and 1 for pairs with at least one collaboration. Therefore the variable in question may

be used as dependent variable to estimate the probability of collaboration between firms in the districts using what is known in econometrics as *binary regression models for dyadic data*.[4]

As pointed out above, in our model the observations are dyads and refer to possible collaborative links between firms in the technological districts. The dyadic regression models conceived to deal with such data involve two major econometric issues: *i)* specification of regressors and *ii)* non-independence of observations. Due to the nature of our data, the order of the actors within the pair is unimportant, i.e. $y_{i,j} = y_{j,i}$ for every i and j or, expressed in words, the values of the dependent variable are the same irrespective of the direction of the link. Consequently, also the independent variables are calculated so as to respect the symmetry of the relations and have the same value for pairs (i, j) and (j,i).[5] Following the approach of Fafchamps and Gubert (2007) the variables referring to the characteristics of the actors making up the various pairs (i, j) are calculated either as the absolute value of the difference or as the sum of values of each actor forming the link. This ensures that the regressors do not depend on the order of the i's and j's. The coefficients of variables expressed in absolute values are interpreted as the effect of differences in attributes on $y_{i,j}$ while those of variables expressed as the sum capture the effect of the combined level of attributes. As regards the second issue, the observations are not independent due to the presence of individual-specific factors common to all dyads sharing the same individual. In such cases, the estimates will still be consistent and not asymptotically biased but the standard errors will be inconsistent, cause the presence of heteroscedasticity, with the consequence of an incorrect inference. Lindgren (2010) suggests that all econometric analysis involving dyadic data should handle the heteroscedasticity issue appropriately. To obtain robust standard errors we rely on the method of Fafchamps and Gubert (2007) which corrects not only for the presence of heteroscedasticity but also for the presence of a correlation among the observations involving similar individuals. The method is a two-way clustering extension of the standard heteroscedasticity variance estimator proposed by Conley (1999) and White (1980).[6] The reduced form of the estimated model is as follows:

$$\Pr(Y_{i,j}=1) = \Lambda[\beta_0+\beta_1(District_{i,j})+ \beta_2(Traditional_{i,j})+\beta_3(Network_{i,j})+\beta_4(Control_{i,j})+\varepsilon_{i,j}]$$

The maximum likelihood method is used to estimate the coefficients.

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[4] For in-depth treatment of econometric models with discrete dependent variables, see Maddala (1983) or Long and Freese (2006).

[5] Summing the observations of the districts included in the sample and only considering the unique pairs between firms yields 3042 possible pairs of actors. Of these observations, about 32% have the value 1. In other words, about 32% of the pairs established at least one collaboration in the district projects.

[6] The formal discussion of the method is beyond the scope of this paper; for more details see Fafchamps and Gubert (2007) or Lindgren (2010).

The motivations underlying the choices of collaboration among firms have been analysed in many theoretical and empirical studies. Following Belderbos *et al.* (2004) reference can be made to two approaches: the Industrial organization approach on firms' cooperation choices, chiefly of a theoretical nature, emphasised technological knowledge, identifying knowledge spillovers (Jaffe, 1986; Cassiman and Veugelers, 2002) and imperfect appropriability (d'Aspromont and Jacquemin, 1988; Shapiro and Willig, 1990) as the main factors leading to collaboration choices among firmschiefly; the second analyses the factors determining cooperation from the angle of transaction costs and Resource-Based Theory, and is more interested in aspects concerning the sharing of costs and risks which are typical of R&D.

Recently, another strand of contributions has suggests the importance of two new dimensions able to affect cooperation in R&D, derived from social network theory and geography of innovation (Maggioni and Uberti, 2011). Of the former, Bala and Goyal (2000) state that the involvement of actors within social networks, thanks to the creation of positive externalities, entails greater benefits than the case of bilateral links. From this point of view, the positioning of organisations within innovative networks is considered the decisive key to cooperation insofar as it increases the benefits of knowledge transfer and appropriability. In relation to innovation geography, Audretsch and Feldman (2004) stress that geographical proximity has a positive effect on cooperation among organisations as it enables closer and more frequent interpersonal relations which, in turn, boost knowledge transfer, especially of a tacit nature. To support such theoretical propositions, some studies which analyse research projects funded by the European Union Framework Programmes (Paier and Scherngell, 2011; Autant-Bernard et al., 2007; Defazio et al., 2008) provide empirical evidence on the importance both of geographical aspects and network effects.

The explanatory variables of the model proposed in this work were chosen *i)* as to take account of the specific nature of the phenomena being studied, i.e. the peculiarities of TDs, *ii)* in line with the literature cited above.

4.3 Explanatory variables

4.3.1 Characteristics of technological districts

The first group of regressors ($District_{i,j}$), which may be considered as that including the main variables of interest, refers to the characteristics of each TD. Mele *et al*. (2008) elaborate a theory to interpret the evolution of TDs based on the importance of governance: to promote the development of the district, the governance authority plays a decisive role in setting out a common policy for the various stakeholders involved which, by their very nature, bring divergent objectives to the district. Further, Wincent *et al.* (2012), in analysing government-funded innovative networks in Sweden, provide empirical evidence concerning the important role played by governance in determining the innovative performance of enterprises. Leven et al. (2014) show the importance of network configuration and orchestration of partnerships between participants for the effectiveness of a large-scale government sponsored program that was designed to increase competitiveness and accelerate economic growth in Northern Sweden.

To allow for the importance of governance, we thus constructed a dichotomous variable (*Governance*) which takes the value 1 if the occurrence of collaboration in district projects is left mainly to the spontaneous action of the various actors (market logic), and 0 if the choice of actors to involve in projects is chiefly guided by the specific will of the governance authority (hierarchical logic). More in details, each TD was assigned to one of the two categories by combining the following information: i) availability on the part of the TD of their own research structures, ii) management characteristics emerging from reading the Articles of Association, iii) information emerging from interviews with TD directors. Indeed, what clearly differentiates the TDs is how the networking activity among participants is implemented. Some governance authorities operate to create strong leadership in order to exert well-defined supervision over all activities in the district. Such districts represent knowledge integrators that design and develop specific network mechanisms to promote links between scientific research and companies, selecting organisations and promoting partnerships to steer the path of development. Districts adopting such a governance of relations among stakeholders are classified as TDs with hierarchical governance. Instead, other governance authorities manage the district in more general terms, focusing on resources and activities rather than on the formation of relationships among actors: they predict the main trends regarding research, support government authorities in planning public financing for R&D and sponsor research projects. Such districts do not carry out ex-ante coordination mechanisms of stakeholders' relations and much less choose the individual actors that will participate in research projects. Districts in which relations are based on individual and spontaneous actions of stakeholders are classified as TDs with market-oriented governance.

A second variable (*University)* measures the weight of university institutions within the various technological districts. The positive effect of collaboration with universities on firm innovation is stressed by much of the economics literature. Establishing collaboration with universities allows firms both to reduce the costs and risks of conducting R&D, and to acquire new knowledge able to further boost their own innovative capacity. Brostrom and Loof (2008) also find empirical evidence that cooperation with university institutes allows firms to strengthen links with other firms, thanks to an improvement in their human capital and their capacities to internalise external opportunities.

4.3.2 Traditional factors

The second vector of covariates $Traditional_{i,j}$ chiefly refers to the characteristics of the individual firms forming the various pairs. An important aspect in determining cooperation choices, which falls within traditional factors, is the complementary nature of knowledge and skills of the various actors (Arora and Gambardella, 1990), especially in high-tech content. Such heterogeneity may promote diffusion of information and the sharing of indispensable resources for the innovative process.

Besides, a low level of heterogeneity could establish competitive dynamics among firms and limit their cooperation (Katz, 1986) in the moment in which there may be competition among such firms on the product market.

Such considerations suggest the existence of a positive link between the propensity to collaborate and the heterogeneity of the firms involved. However, such an effect does not appear generally to hold either at the theoretical or empirical level. For example, Cantner and Meder (2007) find the opposite effect, i.e. that technological proximity, hence greater homogeneity among firms, has a positive effect on collaboration in research in high-tech sectors.

We believe it is worth making a distinction between the concepts mentioned above. For this purpose, to measure the degree of technological and product market proximity between firms participating in TDs we introduced the variables *Technological Proximity* and *Market Competition.* The former is a proxy of sectoral proximity and is calculated as in Caloffi *et al.* (2013). In particular, the variable assumes the value 1 if firm *i* operates in the same two-figure Ateco sector as firm *j*, and 0 otherwise.[7]

By contrast, the *Market Competition* variable aims to take into account the firms' retail market proximity and is the interaction term between the proxy of technological proximity and the variable *Geographical Proximity,* a dichotomous variable which is equal to 1 if the firms of the pairs have their head office in the same province (NUTS 3 level). Hence, the category encoded with 1 of the *Market Competition* variable comprises firms that could compete with one another since they are localized in the same province and belonging to the same industry.

The regressor *Geographical Proximity* also allows for the effect of spatial proximity on the probability of collaboration. Indeed, the importance of geographical proximity is highlighted by several studies which, in various forms, point to localized knowledge spillovers, i.e. the existence of

[7] The classification used is Ateco 2007 at the division level. It should be pointed out that the classification in question does not contemplate all the business sectors in which our sample of firms operates (for example, there is no category for biotechnology). However, this does not generate practical problems for our purposes where what concerns us is whether both components of the pairs operate in the same sector and not the specific sector as such.

positive externalities in space, as an important factor to promote and boost the innovative activity of firms (Breschi and Lissoni, 2001).

The ability of TDs to foster R&D cooperation between small firms is represented by *Small Firms*, a dichotomous variable equal to 1 if both firms of the pair are small organisations with an annual turnover below 10 million euro.

The vector of covariates also comprises the variable *Research Potential* with which allowances are made for the fact that individual actors, in order to obtain a greater transfer of information, seek to collaborate with others that have high research potential, hence a possible baggage of knowledge. By contrast, the *Research Gap* variable refers to the absorptive capacity, i.e. the capacity of organisations to recognise the value of external knowledge and to assimilate it, thereby maximising the benefits derived from technology transfer. This learning process is not without its costs and usually presupposes resources that already exist within the firm (Barney *et al.*, 2001). As stressed by Cohen and Levinthal (1990), an organisation's learning capacity depends greatly on its previous level of specific knowledge. Moreover, the two authors provide empirical evidence for the negative effect of the gap between each organisation's learning capacity on the benefit derived from cooperation in R&D. Both regressors are calculated according to Autant-Bernard *et al.* (2007), i.e. as the sum of the projects in which firms *i* and *j* participated (*Research Potential*), and as the difference in absolute value, the second (*Research Gap*). On the basis of previous considerations, we expect a positive sign in the first case and negative in the second. In order to examine in greater depth the relationship between absorptive capacity and probability of collaboration, we introduce in the model further variables that refer to the gap between firms in age (*Age Gap*), size (*Size Gap*) and patent applications (*Patent Gap*). The latter variable, used in Nooteboom *et al.* (2007), can be considered a proxy of firms' technological capital.

4.3.3 Network effects

The third group of explanatory variables ($Network_{i,j}$) refers to network effects and concerns the variables relative to the position of firms within their own cooperation network. The network graph for each TD is shown in Appendix B. To date there are few studies which verify whether the characteristics of a network affect the collaboration choices of firms on the same network or, to use a term from social network analysis, of their own nodes. Goyal *et al.* (2006), for example, show that the degree of involvement of organisations within their own network, what in the literature is called structural embeddedness (Granovetter, 1985; Uzzi, 1997), is a key factor in explaining cooperation choices. Underlying this result is the idea that knowledge transfer may be achieved not only through direct collaboration between two actors, but also through indirect links which involve all the actors of a whole collaboration network.

To allow for the position of the firms within the network we use three indicators from social network analysis: betweenness centrality, degree centrality and closeness. Betweenness centrality identifies an organisation's position within a network in terms of its ability to make connections with other pairs or groups in a network. An actor with a high degree of betweenness generally holds a favoured position in the network and has greater influence. Degree centrality indicates to what extent an actor is connected via direct links with other actors and is generally the hallmark of active players on the network that often assume the role of hub (Bonaccorsi and Giuri, 2001; Powell *et al.*, 1996). In innovative networks degree centrality could be interpreted as a measure of the propensity of each actor to cooperate. In other words, a high degree centrality at time t may result in a higher collaboration probability at time $t+1$ (Borgatti, 2005).

The third indicator, closeness, measures for each actor the closeness to other network actors (Freeman, 1979). A high level of closeness indicates that an actor is able to reach other network actors more rapidly; in the context of R&D collaboration, this concept means that actors with a high closeness value have a greater probability of receiving knowledge flows and hence, as stressed by Borgatti (2005), of developing innovations before others. The regressors are calculated both as the sum (variables *Betweenneess*, *Degree*, *Closeness*) and absolute difference (*Betweenneess Gap*, *Degree Gap*, *Closeness Gap*) of the values of firms i and j forming the pairs. The indicators have some similarities with the variable that refers to research potential. Indeed, indicators of centrality can be thought of as further proxies, in terms of position within their network, of firms' research potential and absorptive capacity. In addition, from the standpoint of social network analysis, *Research Potential* is a measure of centrality in two-mode networks, while degree centrality and closeness measure the centrality of actors in a one-mode network. A positive sign is expected for the variables expressed as the mean while a negative sign is expected when their expression is the absolute difference.[8] We also note that the indicators of centrality are highly correlated. Thus in the next section we present only the estimates obtained with *Betweenness* and *Betweenness Gap*, the estimates being very similar with degree and closeness indicators. Moreover, Paier and Scherngell (2011) provide empirical evidence concerning the positive effect of long-term relations and mutual knowledge on trust between organisations, and hence, on their propensity to establish strategic collaboration in R&D. To capture this aspect we inserted in the model the dichotomous variables

[8] To limit the possible distorting effect on the estimates due to endogeneity problems, the indicators refer to the networks originating from collaboration in projects on the part of all district stakeholders. Such networks are thus broader than those considered in our sample, which refers only to collaboration between firms. In addition, only projects started in the first two years of the whole period are considered.

Interlocks and *Shareholding*. The former refers to interlocking directorates, i.e. the practice of members of a corporate board of directors serving on the board of multiple corporations. Mizruchi (1996) argue that interlocks are a powerful indicator of network ties between firms and yield significant insight into the behaviour of firms. The variable assumes the value 1 if the firms in the pair share a director or an executive, and 0 otherwise. The second variable is equal to 1 if a firm owns a stake in the other firm of pairs. Since long-term relations favour reciprocal learning and enhance the degree of trust between organisations, we expect a positive sign.

4.3.4 Controls

Finally, the group of control variables ($Controls_{i,j}$) includes: *Actors* representing the number of actors that participate in the districts and that can be considered as a proxy of network size; *Projects* which measures the number of projects activated by each district, and hence the number of potential collaborations that each actor i may establish with the other actors j of the district; *Funds* which refers to the amount of financing distributed to each district for research projects. The latter variable is built using information provided by the districts that, in many cases, are estimates of the total resources available and cannot be attributed to individual projects. Most of the financing is public but the data do not allow distinction between private and public sources. Table 1 provides summary statistics of variables used in the econometric model.

Table 1. Descriptive statistics of variable used in the econometric analysis

	Mean	Std. Dev.	Min.	Max.
Panel A: variables related to pairs				
Y	0.32	0.46	0	1
Research Potential	2.48	1.48	0	12
Research Gap	0.83	1.05	0	7
Technological Proximity	0.83	0.37	0	1
Market Competition	0.54	0.49	0	1
Small Firms	0.37	0.48	0	1
Size Gap	0.73	3.52	0	37.73
Age Gap	2.36	1.10	0	5.16
Patent Gap	-0.07	2.56	-9.13	9.2
Interlocks	0.05	0.07	0	1
Shareholding	0.01	0.11	0	1
Betweenness	0.61	1.18	0	9.04
Betweenness Gap	0.52	1.01	0	5.17
Geographical Proximity	0.33	0.47	0	1
Panel B: variables related to technological districts				
Governance	0.54	0.49	0	1
University	0.26	0.18	0.15	0.43
Projects	9.77	2.72	7	15
Actors	81.15	24.30	26	135
Funds	56.66	21.25	24.72	80.20

5. Results

It may be noted from the correlation matrix reported in Appendix B that centrality indicators are highly correlated with variables *Research Potential* and *Research Gap*. We therefore estimate alternatively their effects on the probability of collaboration: the first column refers to the specification with *Research Potential* and *Research Gap* while Column (2) includes *Betweenness* and *Betweenness Gap*. Lastly, Column (3) reports the estimates of the more parsimonious specification where network indicators, as well as *Research Potential* and *Research Gap,* are excluded. Such model specification avoids any possible problem of milticollinearity incidental to the network indicators. Column (4) reports the coefficients of the standardised explanatory variables. The latter have a more straightforward interpretation than logit coefficients and allow us to capture the importance of the regressors in explaining the dependent variable.[9]

Sectoral and geographical proximity show a positive sign of coefficients but are not statistically significant. With respect to the first result, it seems that the propensity to collaborate is unaffected by the technological proximity of firms. This is at odds with other empirical studies (Caloffi *et al*., 2013; Paier and Scherngell, 2011) that show that research spillovers are greater among firms operating in the same sectors. The result, however, could be due to the lack of appropriateness of our measure. Previous analyses compute the technological proximity in terms of distance between patent portfolios of firms. However, the patenting activity of Italian firms is very low: in our sample 107 out of 179 firms (59%) had no patents, making it impossible to compute the variable of technological proximity in this way.

With respect to size, the variable *Small Firms* is statistically significant, indicating that if both the firms in the pairs are small-sized, then the probability of collaborating increases. This means that districts are successful when encouraging SMEs to cooperate in R&D. In addition, by looking at the *Size Gap* variable, it emerges that districts also play a key role in fostering cooperation between large and small firms. Hence, such results could be interpreted as the effective capacity of districts to create collaborative networks both among small firms and large and small firms. The latter type of cooperation seems of particular interest because, without the intermediation role of governance authorities, large firms would probably be unwilling to form research partnerships with small firms.

The variable *Market Competition* is not statistically significant and presents alternation of signs in the various specifications, excluding that competition on the product market may limit cooperation

[9] The coefficients of the logit model indicate the variation in the log odds of having collaboration after a unit increase of the relative regressors while the standardised coefficients indicate the log-odds variation after a unit increase in the standard deviation of the relative regressors.

between firms.[10] The explanation could lie in the specific nature of TDs compared with other phenomena considered in the economic literature. The latter typically refer to collaborations between firms for individual funding competitions and hence to the forming of temporary consortia. By contrast, a characteristic element of districts is to promote and encourage cooperation between local actors in a long-term perspective. In addition, various projects undertaken by the districts may be classified as basic research projects which, by their very nature, are less subject to generating competitive tensions on the part of finished products. Lastly, technological districts can be thought as precompetitive innovation networks, which participants are not engaged in market competition.

The regressors *Research Potential* and *Research Gap* show the expected sign and strong statistical significance. Both R&D potential and absorptive capacity of *i* and *j* matter. The effect of absorptive capacity is confirmed also looking at variables *Age Gap* and *Patent Gap* that are statistically significant and with the negative signs. The more two firms differ in R&D potential, age and patenting activities, the less they collaborate.

As regards to network variables, the coefficients of *Betweenneess* is statistically significant, with the expected signs, indicating that within innovative networks the firm i draws benefits not only from bilateral relations with other firms j, but also from its own network of collaborations and indirectly from those of each firm j. In addition, the negative sign associated to *Betweenness Gap* further supports the role of similarity between firms, in terms of their position within the network, in fostering the probability of forming a link. Previous knowledge between firms (prior acquaintance) positively affects the probability of collaboration. As shown by the *Interlocks* variable, firms that share a director or an executive have a higher probability of collaborating in the research project of the district. This finding underlines the important role of personal ties in strengthening R&D collaborations. By contrast, the variable *Shareholding* is not statistically significant.

The variables referring to district characteristics provide interesting indications for the particular phenomenon in question. *Governance* has a positive sign and high statistical significance. This could suggest that the activity of intermediation on the part of the governance authority plays a non-secondary role upon firm propensity of collaborating if it is more oriented towards market logic. For example, districts characterised by sizeable redistribution of public funds have a higher capacity to promote cooperation among participating firms.

[10] A negative link, albeit not statistically significant, between market proximity and research output was found by Branstetter and Sakakibara (2002) with regard to Japanese research consortia. Our result, however, could be due to the inappropriateness of the proxy that we use to account for the market competition.

Moreover, the presence of universities also serves to promote collaboration among actors of the district. The interpretation is twofold. On the one hand, R&D cooperation with universities entails strong advantages in terms of cost and risk reduction, as well as in terms of knowledge creation and transfer. On the other hand, the participation of large and prestigious universities in the districts may attract more financing, whether public or private, thereby increasing the probability of collaboration among firms.

The standardised coefficients reported in Column (4) indicate that districts variables, and *Governance* in particular, have the highest explanatory power within the model. Therefore, the characteristics of individual districts play a fundamental role in determining the cooperation propensity among network firms.

Finally, control variables are statistically significant. The regressors *Actors* and *Funds* have a positive sign, showing that in larger districts with more research funds the firms have a higher probability to cooperate in R&D activities. By contrast, the variable *Projects* has a negative effect on the propensity to collaborate, which is surprising since one might expect that the greater the number of projects, the greater would be the probability of forming partnerships among firms.

Table 2. Logit estimates on the determinants of inter-firm R&D cooperation

	(1)	(2)	(3)	(4)
Technological Proximity	0.10	0.17	0.20	0.07
	(0.173)	(0.191)	(0.195)	
Geographical Proximity	0.59	0.31	0.05	0.02
	(0.243)	(0.332)	(0.252)	
Small Firms	0.38*	0.39*	0.36**	0.06
	(0.215)	(0.232)	(0.212)	
Market Competition	-0.17	0.09	-0.03	-0.01
	(0.287)	(0.294)	(0.243)	
Size Gap	0.04**	0.02*	0.03*	0.10
	(0.021)	(0.012)	(0.018)	
Age Gap	-0.01*	-0.01**	-0.01*	-0.07
	(0.006)	(0.004)	(0.006)	
Patent Gap	-0.04**	-0.03*	-0.05*	-0.14
	(0.020)	(0.018)	(0.030)	
Governance	1.70**	1.59*	1.65**	0.83
	(0.722)	(0.950)	(0.789)	
University	2.67*	2.33*	2.57*	0.28
	(1.541)	(1.39)	(1.512)	
Interlocks	1.55*	1.97**	1.94**	0.14
	(0.901)	(0.975)	(0.960)	
Shareholding	-0.45	-0.61	-0.64	-0.07
	(0.544)	(0.520)	(0.454)	
Research Potential	1.41***	-	-	
	(0.191)			
Research Gap	-0.90***	-	-	
	(0.209)			
Betweenness	-	2.46***	-	
		(0.478)		
Betweenness Gap	-	-1.65***	-	
		(0.494)		
Projects	-0.36***	-0.22**	-0.27**	-0.74
	(0.110)	(0.108)	(0.118)	
Actors	0.02***	0.01*	0.01**	0.39
	(0.006)	(0.007)	(0.007)	
Funds	0.03**	0.05**	0.05**	1.20
	(0.014)	(0.023)	(0.024)	
Observations	2923	2923	2923	
Pseudo R^2	0.27	0.23	0.18	
Wald χ^2 (p-value)	0.00	0.00	0.00	

***, **, * Statistically significant at 1, 5 and 10% level. Constant not reported.
Standard errors corrected for dyadic correlation of errors in parenthesis.

Having found that the *Governance* variable has a strong direct effect in fostering R&D collaborations, we also investigate whether the variable affects the relationship between the other regressors and the probability of cooperation. To this aim, we split the sample in two subsamples: one for collaborations implemented in districts with governance oriented towards market logic (estimates in Column 2 of Table 3), and one for collaborations implemented in districts with a more hierarchical governance (estimates reported in Column 1 of Table 3). The check is based on the model specification of Table 2 - Column (1), which has the major advantage to avoid multicollinearity and endogeneity problems between networks indicators and other regressors.[11]

[11] Given that in each of the subsamples there are only 3 TDs, the controls *Projects*, *Actors* and *Funds* have been dropped from the model. We also exclude the variable *University*, concentrating the analysis only on factors related to firms.

The most interesting differences emerge with respect to geographical proximity and the proxies of absorptive capacity. Geographical proximity between firms is not statistically significant in Column (1), while it is significant, with a positive coefficient, in Column (2). Such finding indicates that when the collaborations are more spontaneous, or in other words are formed without a clear guide of the governance authority that manage the districts, firms tend to cooperate with other firms which are localized in the same province. Instead, TDs with hierarchical governance seem to stimulate R&D cooperation also between firms localized far away.

As regards the proxies of absorptive capacity, the variables *Patent Gap* and *Age Gap* are statistically significant only in the subsample of market-oriented governance, while in the subsample of hierarchical governance they are not. This suggests that absorptive capacity is an important determinant of the probability of cooperation most of all in the TDs managed under a governance oriented towards market logic.

On the other hand, in TDs managed with governance of hierarchical type personal ties between firms appear more relevant than in other TDs. The variables *Interlocks* and *Shareholding* are significant at the 1% level and positively correlated with the dependent variable.

Lastly, it is interesting to observe that the variable *Size Gap* is statistically significant in both subsample, but has a positive impact on the probability of cooperation in the case of hierarchical governance, while it has a negative impact in the case of market-oriented governance. Then, firms tend to cooperate with similar partners, in term of size, if the collaborations are spontaneous, while the TDs characterized by a hierarchical type of governance seem to be able to foster research partnerships also between firms of different size.

Table 3. Moderating effect of the district governance on the relationship between individual determinants and the probability of cooperation

	(1)	(2)
Technological Proximity	0.32	-0.00
	(0.213)	(0.190)
Geographical Proximity	-0.49	1.01***
	(0.423)	(0.280)
Small Firms	0.64***	0.35**
	(0.178)	(0.177)
Market Competition	-0.17	-0.11
	(0.275)	(0.387)
Size Gap	0.07***	-2.96***
	(0.025)	(0.434)
Age Gap	-0.00	-0.00
	(0.006)	(0.003)
Patent Gap	-0.00	-0.13***
	(0.028)	(0.036)
University	-0.51	7.41***
	(0.819)	(2.902)
Interlocks	3.51***	0.63
	(1.36)	(1.345)
Shareholding	1.15***	-0.39
	(0.415)	(0.598)
Research Potential	1.71***	1.44***
	(0.126)	(0.118)
Research Gap	-0.77***	-0.94***
	(0.142)	(0.121)
Observations	1608	1315
Pseudo R^2	0.24	0.31
Wald χ^2 (p-value)	0.00	0.00

6. Conclusions

The present paper has analysed the factors that lead to R&D cooperation among firms in Italian government-sponsored TDs. In particular, the analysis has considered firms' participation in some collaborative research projects implemented within TDs. To this aim, a sample of TDs has been investigated by means of a logistic regression model for dyadic data. The main results indicates that the structural characteristics of each district greatly affect the behaviour of the actors concerned. Indeed, estimates showed that the presence of universities may boost cooperation among the firms and that district governance has a major role, in the sense that TDs with market-oriented governance are more successful in fostering cooperation than districts with hierarchical governance. Such a result, although lacking a clear theoretical basis, could indicate that market logic for the coordination of stakeholders participating in TDs has to be preferred if, as stated by the Articles of Association of some TDs, a key goal is to promote the creation of collaborative networks in R&D activities.

Moreover, our findings in part confirm what has been stressed by the traditional literature on the subject. Knowledge transfer and absorptive capacity of firms are important factors in explaining decisions to cooperate. However, these aspects have less direct impact than the structural characteristics of individual districts. Such evidence suggests that, within innovation networks where there is a governance body, such as Italian TDs, the latter's intermediation may attenuate in part the importance of factors that explain cooperation in spontaneous research networks. Given such consideration, we have analysed more in-depth the role of governance and its moderating effects on other determinants of R&D cooperation. In this respect, relevant differences emerge when we compare TDs with different types of governance. In the TDs characterized by a governance oriented towards market logic, the determinants of inter-firms R&D cooperation within TDs are consistent with the traditional literature. For example, geographical proximity and absorptive capacity have a significant impact on the probability of cooperation. On the other hand, in the TDs with hierarchical governance the collaborations between firms seem to be driven by other factors, such as personal ties; geographical proximity does not have any effects, while absorptive capacity affects the probability of collaboration to a lesser extent.

In addition, other findings shed light on several interesting features of TDs. Technological proximity does not appear to affect the probability of collaborating among firms, contrasting with part of the empirical and theoretical works concerning cooperation in high-tech activities. Finally, also network effects, captured in the estimates with position indicators from social network analysis and prior acquaintance, play a key role in determining collaboration among firms.

Some interesting considerations about TDs as an instrument of public policy also emerge from the analysis. The estimates showed that TDs, by setting up collaborative networks in research projects, are able to promote the collaboration of small firms both with one another and, in the case of TDs characterized by hierarchical governance, with large firms. From this point of view the districts seem to achieve one of their main objectives concerning the engagement of small firms in research and development. Furthermore, small firms can draw considerable advantage from research partnerships with large firms which, without the intermediation role of the districts, would be unlikely to take place. Based on the present analysis, it could be argued that if one of the main object of a TD is to foster R&D cooperation between small and large firms, then a governance of hierarchical type may be preferred. On the other hand, if the main object is to stimulate collaborations among small firms, then a market-oriented governance may be more appropriate.

Our analysis is the first stage in the characterisation of R&D cooperation and in the identification of its drivers within Italian TDs. The individual determinants considered here still need to be investigated in depth. However, in our opinion, the results constitute a useful starting-point for analysing the complex reality of TDs. Future studies could – and should – also deal with assessing their achievements and those of the public policy which led to their birth. This undertaking appears both stimulating and arduous. Indeed, it should not be forgotten that technological districts represent an experience which is still evolving and that the effects of R&D, as well as the economic returns tied to innovations, are only fully achieved in the long term.

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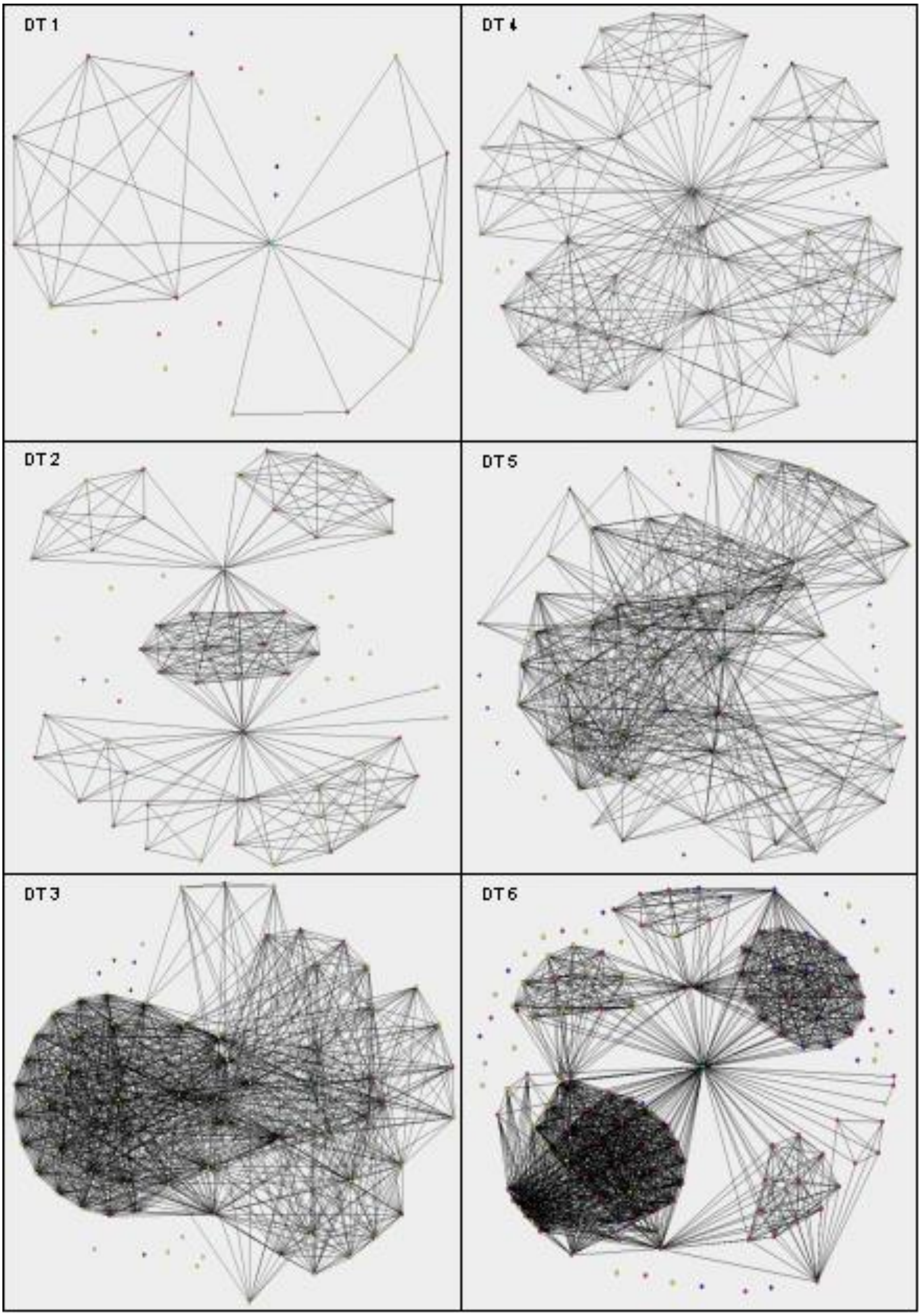
Appendix A – The collaborative research networks within the TDs included in the sample



Appendix B – Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) Technological Proximity	1.00																	
(2) Geographical Proximity	0.06*	1.00																
(3) Small Firms	0.10*	0.20*	1.00															
(4) Market Competition	0.21*	-0.38*	-0.33*	1.00														
(5) Research Potential	0.08*	0.11*	-0.01	-0.02	1.00													
(6) Research Gap	0.00	-0.04*	-0.14*	0.05*	0.33*	1.00												
(7) Size Gap	0.05*	0.00	-0.16*	0.08*	-0.02	0.02	1.00											
(8) Age Gap	-0.01	-0.12*	-0.28*	0.11*	0.03	0.08*	0.11*	1.00										
(9) Patent Gap	-0.02	-0.05*	0.00	-0.00	0.02	0.04*	-0.10*	0.10*	1.00									
(10) Betweenness	0.04*	0.10*	-0.01	-0.04*	0.70*	0.54*	-0.01	0.06*	-0.02	1.00								
(11) Betweenness Gap	0.05*	0.07*	0.00	-0.03*	0.63*	0.62*	-0.02	0.04*	-0.00	0.71*	1.00							
(12) Governance	-0.00	0.30*	0.13*	-0.26*	-0.32*	-0.26*	-0.01	-0.13*	-0.16*	-0.21*	-0.21*	1.00						
(13) University	-0.03	-0.12*	-0.29*	0.15*	-0.34	-0.01	0.07*	0.11*	0.02	-0.25*	-0.25*	0.11*	1.00					
(14) Interlocks	0.02	-0.00	-0.03*	0.01	0.04*	0.04*	-0.00	-0.00	-0.00	0.00	0.00	-0.02	0.00	1.00				
(15) Shareholding	0.01	-0.02	-0.06*	0.02	0.03	0.03*	-0.01	-0.01	0.02	-0.00	-0.00	-0.06*	-0.01	0.38*	1.00			
(16) Projects	-0.02	0.10*	-0.12*	-0.06*	-0.36*	-0.11*	0.14*	-0.07*	-0.09*	-0.29*	-0.29*	0.49*	0.60*	0.02	-0.02	1.00		
(17) Actors	0.01	0.09*	-0.05*	0.01	-0.21*	-0.06*	-0.09*	-0.06*	-0.09*	-0.10*	-0.09*	0.38*	0.38*	-0.03	-0.04*	0.56*	1.00	
(18) Funds	0.02	-0.15*	0.07*	0.12*	0.46*	0.21*	-0.02	0.05*	0.11	0.30	0.30*	-0.39*	-0.51*	0.02	0.07*	-0.55*	-0.36*	1.00