The Network of EU-Funded Collaborative R&D Projects

M. J. Barber
Centro de Ciências Matemáticas, Universidade da Madeira, Funchal, Portugal

A. Krueger and T. Krueger
Universität Bielefeld, Bielefeld, Germany

T. Roediger-Schluga
ARC systems research, Vienna, Austria

(Dated: October 21, 2018)

We describe collaboration networks consisting of research projects funded by the European Union and the organizations involved in those projects. The networks are of substantial size and complexity, but are important to understand due to the significant impact they could have on research policies and national economies in the EU. In empirical determinations of the network properties, we observe characteristics similar to other collaboration networks, including scale-free degree distributions, small diameter, and high clustering. We present some plausible models for the formation and structure of networks with the observed properties.

I. INTRODUCTION

Real world network analysis has become a major issue of research in the last years. Most prominent are perhaps the investigations of the structure of the World Wide Web, the network of internet routers, and certain social networks like citation networks. On the theoretical side, one tries to understand the mechanisms of formation of such networks and to derive statistical properties of the networks from the generating rules. On the rigorous mathematical side, there are only a few results for specific models, indicating the difficulty of a purely mathematical approach (for a survey of recent results in this direction, see [7]). Thus, the main approach is to use some mean field assumption to get relevant information about the corresponding graphs. Although it is not clear where the limits of this approach lie, in many cases the results match well with numerical simulations and empirical data.

In this article, we study a particular collaboration network. Its vertices are research projects funded by the European Union and the organizations involved in those projects. In total, the database contains over 20000 projects and 35000 participating organizations. The network shows all the main characteristics known from other complex network structures, such as scale-free degree distribution, small diameter, high clustering, and inhomogeneous vertex correlations.

Besides the general interest in studying a new, real-world network of large size and high complexity, the study could have a significant economic impact. Improving collaboration between actors involved in innovation processes is a key objective of current science, technology, and innovation policy in industrialized countries. However, very little is known about what kind of network structures emerge from such initiatives. Moreover, it is quite likely that network structure affects network functions such as knowledge creation, knowledge diffusion, and the collaboration of particular types of actors. Presumably, this is determined by both endogenous formation mechanisms and exogenous framework conditions. In order to progress in our understanding, it is therefore essential to have sound statistics on the structure of networks we observe and to develop plausible models of how these are formed and evolve over time.

The model networks we use to compare with the empirical data are random intersection graphs, a natural framework for describing projections of bipartite graphs. Discrete intersection graphs similar to the ones we use were first discussed in [8]. We extend and refine the construction from [8] to be more applicable to real world graphs.

Perhaps the most important finding from our model approach is the strong determination of the real network structure by the degree distribution. That is, most statistical properties we measure in the EU research project networks are the ones observed in a typical realization of a uniform weighted random graph model with given (bipartite) degree distribution as in the EU networks. Since this distribution is characterized by two exponents—one for each partition—we have essentially only four parameters (size, edge number, and exponents) which are needed to describe the entire network. This is a tremendous reduction of complexity indicating that only a few basic formation rules are driving the network evolution.

In section II we describe the preparation of the data on the EU research programs. We present empirical determination of the network properties in section III followed by an explanation of these properties using a random intersection graph model in section IV. Finally, in section V we summarize the key results and consider implications of the network properties on EU research programs.
II. THE DATA SET

In this work, we study research collaboration networks that have emerged in the European Union’s first four successive four-year Framework Programs (FPs) on Research and Technological Development. Since their inception in 1984, six FPs have been launched, on four of which we have comprehensive data. FPs are organized in priority areas, which include information and communication technologies (ICTs), energy, industrial technologies, life sciences, environment, transportation, and a number of additional activities. In line with economic structural change, the main thematic focus of the FPs has shifted somewhat over time from energy and industrial technologies to the application of ICTs and life sciences. The majority of funding activities are aimed at stimulating research partnerships between firms, universities, research organizations, governmental actors, NGOs, lobby groups, etc. Since FP4, the scope of activities has been expanded to also cover training, networking, demonstration, and preparatory activities (for details, see reference [1]). In order to keep our data set compatible over the different FPs, we have excluded the latter set of projects from FP4 and only focus on collaborative research projects (see table I).

In order to receive funding, projects in FP1 to FP4 had to comprise at least two organizations from at least two member states. We have retrieved data on these projects from the publicly available CORDIS (Community Research and Development Information Service) projects database [10]. This database contains information on all funded projects as well as a reasonably complete listing of all participating organizations.

The raw data on participating organizations is rather inconsistent. Apart from incoherent spelling in up to four languages per country, organizations are labelled inhomogeneously. Entries may range from large corporate groupings, such as Siemens, or large public research organizations like the Spanish CSIC to individual departments or labs and are listed as valid at the time the respective project was carried out. Among heterogeneous organizations, only a subset contains information on the unit actually participating or on geographical location (address, city, region and/or country). Information on older entries and the substructure of firms tends to be less complete.

Because of these difficulties, any automatic standardization method akin to the one utilized by Newman [9] is inappropriate to this kind of data. Rather, the raw data has to be cleaned and completed manually, which is an ongoing project at ARC systems research. The objective of this work is to produce a data set useful for policy advice by identifying homogeneous, economically meaningful organizational entities. To this end, organizational boundaries are defined by legal control and entries are assigned to the respective organizations. Resulting heterogeneous organizations, such as universities, large research centres, or conglomerate firms are broken down into subentities that operate in fairly coherent areas of activity, such as faculties, institutes, divisions or subsidiaries. These can be identified for a large number of entries, based on the available contact information of participants, and are comparable across organizations.

The case of the French Centre National de la Recherche Scientifique (CNRS), the most active participant in the EU FPs may serve as an illustration. First, 785 separate entries were summarized under a unique organizational label. Next, these 785 entries were broken down into the eight areas of research activity in which CNRS is currently organized. Based on available information on participating units and geographical location, 732 of the 785 entries could be assigned to one of these subentities. For the remaining 53 entries, the nonspecific label CNRS was used.

Comparable success rates were achieved for other large public research organizations and universities. Due to scarcer information, firms could not be broken down at a comparable rate. Moreover, due to resource constraints, standardization work has focused on the major players in the FPs. Organizations participating in fewer than a total of 30 projects in FP1–4 have not been broken down yet. Due to these limitations in processing the data, we cannot rule out the possibility of a bias in analysing our data. However, we have run all the reported analyses with the undivided organizations and have obtained qualitatively similar results, apart from different extreme values, e.g., maximum degree.

Table II displays information on the present data set, which contains information on a total of 27,758 projects, carried out over the period 1984 to 2004. It shows that the total budget as well as number of funded projects has increased dramatically from FP1 to FP4. Moreover, it provides a rough measure on the completeness of the available data. For a sizeable number of projects, the CORDIS project database lists information only on the project co-ordinator. This is due to the age of the data and inhomogeneous disclosure policies of different units at the European Commission. Comparing the number of projects containing information on more than one participant with the total number of projects funded in each FP shows that the data is fairly complete as of FP2.

The fact that FP1 was the first program launched and that the available data are rather incomplete make it exceptional in many respects. We therefore focus our analyses on FP2–4 and only give graph characteristic values for FP1 to indicate the difference to the networks created by the subsequent FPs.
III. THE NETWORK STRUCTURE

In this section, we present the basic properties of the network structure for projects and organizations in the first four EU Framework Programs. We consider both graphs as intersection graphs, each being the dual of the other, which, for our purposes, is generally more convenient than the usual bipartite-graph point of view. Recall that an intersection graph is given by an enumerated collection of sets—the vertices of the intersection graph—with elements from a given fixed base-set and edges defined via the intersection property (edge \( \subseteq \) nonempty intersection of two sets). The sets need not be distinct.

We denote by \( \mathcal{P} = \{P_1; \ldots : P_M\} \) the family of projects and by \( \mathcal{O} = \{O_1; \ldots : O_N\} \) the family of organizations. Projects are understood as labeled sets of organizations and organizations as labeled sets of projects. The corresponding intersection-graphs are denoted by \( G_P \) and \( G_O \) and we will sometimes use the terms P-graph and O-graph for them. The size \( |x| \) of a vertex \( x \) from \( G_P \) or \( G_O \) is the cardinality of the set corresponding to the vertex; in the picture of bipartite graphs, the size is just the degree of the vertex. In tables II and III we give some basic parameters measured on the P- and O-graphs from the four Framework Programs. Since the degree distribution for P-graphs is a superposition of two power-law distributions (one for small degree values and one for large values), we give the corresponding values for the exponents parenthetically.

As expected, FP1–4 are of small world type: high clustering coefficient and small diameter of the giant component. There is a slight increase in the clustering coefficient of the O-graphs from FP1 to FP4, indicating a stronger integration amongst groups of collaborating organizations. This is also reflected in the mean project size which increases from 2.4 to 6.2. There is an interesting jump in the P-graph mean degree values and the mean triangle numbers between FP1 and 2 and between FP2 and 3. The maximal degree of the O-graphs are very high in comparison with the mean degree, which is a consequence of the power law degree structure. For the P-graphs, the gap between mean and maximal degree is less pronounced.

More information is contained in the statistical properties of the relevant distributions. The numerical data strongly indicate that the size distributions follow power laws. Also, the O-graph degree distribution is of power-law type, while the project-graph degree distribution is a superposition of two scale free distributions, one dominating the distribution for small degree values (up to 100) and one relevant for the large degree values. We discuss these properties at greater length in the following sections.

A. Size distributions

The size distributions are the basic distributions for the EU-networks since, as will be shown in section section IV, a typical sample from the random graph space with fixed size distributions like in FP 2-4 will have very similar statistical properties to FP 2-4. This strongly suggests that there is essentially no additional correlation in the data once the size distribution is known. Both the O-graph and P-graph size distributions show clear asymptotic power law distributions for FP1–4 (figs. I and II). In terms of the corresponding bipartite graph, these are just the degree distributions of the project and organization partitions. While the O-graph size distribution is of power law type over the whole size range, the P-graph size distribution deviates strongly from the power-law for small size values. In section IV we give a possible explanation for the appearance of the power law distribution for size.

The numerical values for the exponents of the organization size distributions from FP2–4 are slightly below 2, but constant within the error tolerance. This indicates that the distribution of organizations able to carry out a particular number of projects has not changed in the three Framework Programs. A complementary interpretation of this finding is that the underlying research activities, which we know to have changed over time, have not altered the mix of organizations participating in a particular number of projects in each Framework Program. It is further worth noting that the values of the O-graph exponents are close to the critical value 2, hence the size expectation could diverge for large graphs (whether the value is really below 2 or not is still unclear due to the error tolerance).

The picture is similar for the P-graphs, although there are some differences in the initial behavior (that is, for small project sizes) and in the exponent value. The local minima at size 2 is decreasing from FP2–4. This points to the existence of an optimal project size within the regime of the EU FPs. Moreover, the rise in the average project size indicates that increases in the available funding from FP2 to FP4 not only lead to more projects, but also slightly larger projects. This is consistent with recommendations from evaluation studies and the stated attempts of the EU commission to reduce its administrative burden. As a whole, the size distribution for the P-graphs matches in the asymptotic regime very well to a power law with exponent around -3, hence indicating that the mechanisms for coagulation of organizations into a project did not greatly change from FP2–4.
B. The degree distribution

Since the degree distribution in the projection graphs is just the distribution of the size of the 2-neighborhood \( N_2(x) := \# \{ y : d^{bi}(x, y) = 2 \} \), it is not surprising that this quantity is closely connected to the size distribution. In the absence of other special correlations, it can be shown (see section IV) that the degree distribution is determined by the size distribution in a rather simple way. Namely, for the case when both size distributions are scale-free with exponents, say \( \alpha \) (O-size) and \( \beta \) (P-size), the P-graph degree distribution is a superposition of two power-law distributions with exponents \( \alpha - 1 \) (and cutoff given by the maximal O-size value) and \( \beta \). The same holds vice versa for the O-graph.

In figs. 3 and 4 we show the degree-distribution for the P- and O-graphs in a log-log plot. While the organization graphs for FP2–4 show a clear power law, the picture for the project graphs is more complicated. As previously mentioned, the P-graph degree distribution shows two different power laws, one for the initial segment up to degree 150 and another one for large degrees. Nevertheless, there is still a widely scattered heavy tail in the degree distribution. The deviation from a power law in the P-graphs indicates a kind of anticorrelation: large projects above a size of 15 are mainly formed by organizations of small size. A possible explanation is that large projects have a time- and resource-demanding intrinsic network structure, making it more unlikely that a participating organization has other projects (of course, with the exception of hub-like organizations such as CNRS with a priori unlimited capacity).

C. Clustering, correlation and edge multiplicity

By their construction process, intersection graphs have a naturally high clustering coefficient. This is easily seen, since an organization which participates in, say, \( k \) projects generates a complete subgraph of order \( k \) in the P-graph amongst these projects. If the probability for an organization to be in more than one project is asymptotically bound away from zero, it follows that the P-graph (and similarly for the O-graph through an analogous argument) has a nonvanishing clustering coefficient. In the present study, we focus on the triangle number \( \Delta(x) := \# \{ \text{triangles containing } x : x \in (\mathcal{P} \cup \mathcal{O}) \} \) as a measure of local clustering. We define the degree-conditional mean triangle number as \( \Delta_k := E\{\Delta(x) | d(x) = k\} \). As seen in figs. 3 and 4 we have \( \Delta_k \sim k \) for both graph types.

There is a good explanation for this type of behavior in the framework of intersection graphs (see section IV). As noted above, high clustering in intersection graphs is not necessarily an indication of local correlations between vertices. This is already seen in the case of an Erdős-Rényi random bipartite graph where an edge between any project and organization is drawn i.i.d. with probability \( p \). If \( \mathcal{P} \) and \( \mathcal{O} \) are of equal cardinality \( N \) and \( p = \frac{c}{N} \), the expected bipartite degree equals \( c \). For large \( N \) a typical realization of the random graph looks locally like a tree with branching number \( c - 1 \). However, for the projection graphs, we obtain an positive clustering coefficient that is independent of \( N \), since most projects and organizations cause complete graphs of order \( c \) and a typical vertex is therefore a member of \( \sim c \) cliques of order \( c \).

A better indication for the presence of correlations is given by the so-called multiplicity of edges. For a link between two organizations or projects it is sufficient to have just one project or organization, respectively, in common, but of course there could be more. Given an edge \( x \sim y \), we define \( m(x, y) := |x \cap y| - 1 \) and call it the multiplicity of the edge. As will be discussed in the next section, random intersection graphs without local search rules can nevertheless admit a high edge multiplicity. In figs. 7 and 8 the multiplicity distribution is shown for P- and O-graphs of FP2–4. There is an almost perfect power-law behavior with exponent 4.3. Note that positive multiplicity in the projection graphs translates in the bipartite graph picture into the presence of cycles of length four. The presence of exceptionally high multiplicity in the P-graphs may be caused by memory effects due to prior collaborative experience. Also, a greater edge multiplicity may result from the fact that organizations are active in a wider set of complementary activities. In this case, intra-organizational spillovers may also be of importance as search for potential partners may be influenced by the collaboration behavior of other actors within an organization. Such effects should be detectable from a fine structure analysis of the time evolution of the corresponding graphs.

D. Diameter and mean path length

There is essentially no difference in the diameter value of the largest component in the four Framework Program networks. A classical random graph of the same size and the same edge number would have a diameter about \( \log_2 N \). The mean path length is about a third of the diameter and and shows a slightly higher variation between the different framework programs. It is well known that the expected path length in random graphs with a scale free degree distribution and exponent less than 3 is essentially independent of the graph size (the diameter of the largest component still increases in \( N \) but only as \( \log \log N \)). The same holds for random intersection graphs with power law
size and degree distributions. Since the O-graphs seem to fall into that class, the almost constant diameter and path length is not surprising. Although the P-graphs do not show an asymptotic power law structure for the degree, there is a strong increase in the edge density from FP2 to FP4, keeping the diameter of the largest component almost fixed.

IV. A RANDOM INTERSECTION GRAPH MODEL

Intersection graphs are a natural framework for networks derived from a membership relation, such as citation networks, actors networks, or networks reflecting any other kind of cooperation. As previously mentioned, intersection graphs by construction have a high clustering coefficient. As explained below, the clique distribution of a random intersection graph is almost given by the size distribution of the dual graph.

A. Random intersection graphs with given size distribution

One of the simplest random intersection models is constructed in the following way. Knowing the size of a set to be constructed, we generate a random subset from a finite base set \( X = \{a_1, a_2, ..., a_N\} \) of \( N \) elements, such that each set element is drawn i.i.d. uniformly from \( \phi \) when \( X \) is constructed, we generate a random subset from a finite base set. These subsets constitute the vertices of a random graph. Edges are defined via the set intersection property, namely we have an edge between \( i \) and \( j \) (denoted by \( i \sim j \)) if and only if the associated subsets \( A_i \) and \( A_j \) have nonempty intersection (to compare with earlier sections, \( A \) stands here for either projects sets \( P \) or organization sets \( O \)). The size (cardinality) of the subsets is either itself a random variable drawn i.i.d. from a probability distribution \( \varphi(k) \) or given by a list \( \{D_k := \#\{A_i : |A_i| = k\}\} \) (where for each \( i \) a conditional random choice is made to which size class it belongs). For the latter case, we define again \( \varphi(k) := \frac{D_k}{N} \) where \( M \) is the total number of sets to be formed.

Since we want to compare the model with the EU- cooperation network we are mainly interested in the situation when \( \varphi \) is an asymptotic power law distribution

\[
\varphi(k) = \frac{1}{k^{\alpha + o(1)}}; \alpha > 2
\]  

This assumption is also reasonable for many other applications where vertices are formed from a base set of elements. To obtain an interesting limiting random graph space, we further assume that the number of chosen subsets is \( C_1 \cdot N \) where \( C_1 \) is neither too large nor too small (for FP2–4 we have about twice as many organization as projects hence \( C_1 \) is either 2 or 0.5).

A basic quantity for the analysis of intersection graphs is the conditional edge probability given the size of two subsets:

\[
P_{k,l}(N) := \Pr\{i \sim j \mid |A_i| = k \text{ and } |A_j| = l\}
= \Pr\{A_i \cap A_j \neq \emptyset \mid |A_i| = k \text{ and } |A_j| = l\}
= 1 - \frac{{N-k \choose k}}{{N \choose k}}
= 1 - \frac{(N-k)! (N-l)!}{N! (N-k-l)!}
= 1 - \frac{(N-k) (N-k-1) \cdot \cdot \cdot (N-k-l+1)}{N (N-1) (N-2) \cdot \cdot \cdot (N-l+1)}
\]

Using the condition \( lk \ll N \), we obtain

\[
P_{k,l}(N) = 1 - \frac{1 - \frac{k}{N}}{1 - \frac{l}{N}} \frac{1 - \frac{k+1}{N}}{1 - \frac{l+1}{N}} \cdot \cdot \cdot \frac{1 - \frac{k+l-1}{N}}{1 - \frac{l+k-1}{N}}
= 1 - \left(1 - \frac{k}{N}\right) \left(1 - \frac{l}{N}\right) \cdot \cdot \cdot \left(1 - \frac{k+l-1}{N}\right)
= 1 - \frac{1 - \frac{l+k+1}{N}(l+1)(l+2)}{1 - \frac{l}{N}(l+1)(l+2)} + o\left(\frac{1}{N}\right)
= \frac{lk}{N} + o\left(\frac{1}{N}\right)
\]
With this result, we can easily calculate the conditional degree distribution for a vertex of given size. First, we estimate the conditional subdegree distribution with respect to a given group of vertices of size \( m \). Here, the subdegree \( d_m(i) \) of a vertex \( i \) is defined as the number of edges \( i \) has with vertices of size \( m \). Clearly \( d(i) = \sum_m d_m(i) \). We have

\[
\psi_l(k, m) := \Pr \{ d_m(i) = k \mid |A_i| = l \} = \sum_{G} \Pr \{ z \mid |A_z| = m = G \} \left( \frac{G}{k} \right) \left( \frac{ml}{N} + o \left( \frac{1}{N} \right) \right)^k \left( 1 - \frac{ml}{N} + o \left( \frac{1}{N} \right) \right)^{G-k}.
\]

The probability that a randomly chosen vertex \( j \) has size \( m \) equals, by assumption, \( \frac{C_2}{m^{\alpha + o(1)}} \) with normalization constant \( C_2 \quad (1 = \sum_m \frac{C_2}{m^{\alpha + o(1)}}) \). We therefore obtain

\[
\psi_l(k, m) = \lim_{N \to \infty} \left( C_1 N \cdot \frac{C_2}{m^{\alpha}} \right) \left( \frac{ml}{N} + o \left( \frac{1}{N} \right) \right)^k \left( 1 - \frac{ml}{N} + o \left( \frac{1}{N} \right) \right)^{C_1 N \cdot \frac{C_2}{m^{\alpha}}} - \kappa,
\]

which converges to a Poisson distribution

\[
\psi_l(k, m) = \frac{c(m)^k}{k!} e^{-c(m)}
\]

with \( c(m) = m^{1-\alpha} l C_1 C_2 \). Since the distribution \( \psi_l(k) \) of the degree of vertices \( i \) with \( |A_i| = l \) is the convolution of the Poisson distributions \( \psi_l(k, m) \), we obtain again a Poisson distribution for \( \psi_l(k) \):

\[
\psi_l(k) = \frac{c_l}{k!} e^{-c_l},
\]

with \( c_l = \sum_m c(m) = l \cdot C_3 \), where \( C_3 = \sum_m m^{1-\alpha} C_1 C_2 \) is a well defined constant since \( \alpha > 2 \). It remains to estimate the total degree distribution \( \psi(k) \). In \( \mathbb{2} \), conditions were given describing when a superposition of Poisson distributions results in a scale-free distribution. Specifically, we get the following asymptotic estimate:

\[
\psi(k) = \sum_m \varphi(m) \frac{(m C_3)^k}{k!} e^{-m C_3} = \sum_m \frac{1}{m^{\alpha + o(1)}} \frac{(m C_3)^k}{k!} e^{-m C_3}.
\]

The main contribution to \( \psi(k) \) comes from a rather small interval of \( m \)-values, called \( I_{ess}(k) \). This interval has the property that for \( m \in I_{ess}(k) \), the expectation \( \mathbb{E}(d(i) \mid |A_i| = m) \) is of order \( k \). The exponential decay of the Poisson distribution guarantees that the remaining parts of the sum become arbitrarily small for large \( k \). It is important that the constant \( c_l \) has a linear \( l \)-dependence since an \( l \)-proportionality with exponent larger than one would force the degree distribution to have gaps due to a lack of overlap of the individual Poisson distributions. We therefore obtain for the degree distribution a power law with the same exponent \( \alpha \) as in the size distribution.

Although the intersection model gives a power-law degree distribution when the size distribution is already of power-law type, we will not obtain a power-law distribution for the size on the dual graph unless additional assumptions are made on the set formation rules. It is easy to see that the size distribution on the dual graph is asymptotically Poisson. Since \( \Pr \{|x| = k\} \sim \frac{M}{k} \left( \frac{\mathbb{E}(|A|)}{N} \right)^k \left( 1 - \frac{\mathbb{E}(|A|)}{N} \right)^{M-k} \) and \( \mathbb{E}(|A|) \) converges as well as \( \frac{M}{N} \) for \( M, N \to \infty \), we obtain in the limit a Poisson distribution. Nevertheless, the degree distribution on the dual graph still admits a scale-free part induced by the scale-free size distribution of the intersection graph. We will not discuss many of the details, but instead provide a simple estimation for the lower bound on the number of elements \( a_i \) with \( \mathbb{E}(a_i) = k \). Namely, the number of elements \( a_i \) which are members of sets \( A_j \) with \( |A_j| = k \) is for large \( k \) and \( M, N \gg k \) about \( k^M \frac{\text{const}}{N} \). Since \( \mathbb{E}(a_i) \geq k \) for \( a_i \in A_j \) with \( |A_j| = k \), we obtain \( \frac{\text{const}}{N} \) as a lower bound on the density of elements \( a_i \) with degree greater than or equal to \( k \) (note that we assumed \( \alpha > 2 \)). This estimate holds of course only up to the maximal size \( \mathbb{E}(k) \), which is in the range of the power law distribution for the set sizes \( |A_i| \). For larger \( k \)-values there is a rapid exponential decay.

The last argument clarifies also the situation when one wants to impose conditions on the size distribution and the dual size distribution. Without going into the details of the rather involved analysis, we simply state that the
resulting degree distribution is given by a superposition of the size distribution and the dual size distribution (the last one enters with an exponent reduced by one). This explains essentially the picture for the degree distribution for the P-graph.

Finally we want to discuss the mean triangle (conditioned on the degree) - degree dependence which shows a clear linear behavior in the empirical data. We argue that this is again a consequence of the power law distribution for the size. First observe that a size $k$ element $a_i \in A_j$ induces a $k - 1$ complete subgraph on the neighborhood vertices of $A_j$. Furthermore, each maximal $k$–clique in which $A_j$ is a member generates $(k - 1)(k - 2)/2$ triangles for $A_j$. Since the size distribution of the elements $a_i$ is Poisson with expectation of, say, $c$ and the degree of $A_j$ is proportional to the size $|A_j|$, we obtain for the conditional expected number of triangles $\Delta_k$ given the degree $k$:

$$\Delta_k := \mathbb{E}(\#\text{triangles containing } A | d(A) = k) \sim \frac{c^2}{2} \text{const} \cdot k.$$ (17)

In deriving eq. (17), we used the facts that with high probability the size of the intersection between two sets $A_i$ and $A_j$ has cardinality 1 (conditioned on the two sets having a nonempty intersection) and that the Poisson distribution has an exponentially decaying tail.

### B. A Molloy-Reed version of random intersection graphs and a Bernoulli type model

We sketch the construction of random intersection graphs with given size distribution $\varphi$ and size distribution $\psi$ on the dual. The two distributions are not independent but have to fulfill the condition $\sum_j [\varphi(j) - \psi(j)] = 0$. There are further restrictions on the maximal size in order to get a reasonable random graph model. Note that the problem is equivalent to the construction of a random bipartite graph given the degree sequence on the two partitions.

Assign first to each set $A$ and each element $a$ from the base set a random size value according to the given distributions $\varphi$ and $\psi$. Let $D_k$ be the resulting set of elements $a_i$ with size $k$. Replace each element from $D_k$ by $k$ virtual elements $a_{i,l}, l = 1, 2, \ldots, k$ and form a new base set $X'$ with all the virtual elements. The set formation process for the sets $\{A_i\}$ is now the same as in the previous section except that each chosen virtual element $a_{i,l}$ will be removed from $X'$ when it was selected first into a set. After the sets are constructed we identify the virtual elements back into the original ones and define the corresponding set graph in the usual way.

By construction the resulting size distribution on the dual graph will be given by $\psi$ as long as the probability of choosing two virtual elements $a_{i,l}$ and $a_{i,m}$ (corresponding to the same element $a_i$) is sufficiently small. To ensure this one has to impose restrictions on the maximal size values. It is not difficult to show that the correlation between the size of $A$ and the size of an element $a$ is multiplicative. In case of a linear relation between the number of sets $N$ and the number of elements $M$ we have

$$\Pr\{a \in A | |A| = k \wedge |a| = l\} \sim \frac{\text{const}}{N} k \cdot l.$$ (18)

To see this observe that

$$\Pr\{a \in A | |A| = k \wedge |a| = l\} = 1 - \Pr\left\{\text{among the } k \text{ choices to generate } A \text{ is no virtual } a \text{ - element}\right\}$$

$$= 1 - \frac{M^* - l}{M^*} \cdot \frac{M^* - 1 - l}{M^* - 1} \cdot \ldots \cdot \frac{M^* - k - l + 1}{M^* - k + 1}.$$ (19)

with $M^*$ being the number of virtual elements. The last formula has the same structure as the expression for the pairing probability in the previous section hence we get, for $lk \ll M^*$ and bounded first moments of the $\psi$-distribution, the claimed multiplicative correlation. We note that there is also a variant of the Molloy-Reed construction which produces an additive size-size correlation such that $\Pr\{a \in A | |A| = k \wedge |a| = l\} \sim \frac{\text{const}}{N} (k + l)$ holds (see 12 for details of the algorithm).

We next present a simulation-based comparison of the multiplicative and additive Molloy-Reed model with the FP4 network. The input size distributions for the Molloy-Reed simulations are the same as in FP4. For completeness we also include the simulation results based on the simple random intersection graph model defined in the previous section. To make clear which size distribution is given in that case we use the notation P-model (O-model) for the intersection graph with fixed P (O) size distribution and denote by PO-model the corresponding Molloy-Reed graphs since both size distributions are fixed therein. Figs. 12 and 13 show the degree distribution for the O- and P-graphs. There is a very good agreement over the whole range of degree values between the real FP4 network projections and typical samples of the multiplicative Molloy-Reed model. This is quite remarkable since a considerable bias from the almost independence of the Molloy-Reed model should be visible in the degree distributions. The fact that there is no
deviation between the degree distributions indicates that the majority of project-organization alignments is essentially a random process. Furthermore, the additive model reproduces the FP4 P-graph degree distribution only well for large degree values indicating that the correlation is indeed multiplicative.

Two quantities measuring local correlations are the triangle-degree dependence and the distribution of edge multiplicity introduced earlier. Fig. 11 compares the triangle-degree correlation for the O-graph. Although the overall picture is similar (linear dependence up to medium degree) there is a clear tendency for higher triangle numbers in the FP4 for large degree values. Again the multiplicative version matches better with the data than the additive model. The edge multiplicity—again for the O-graphs—is shown in fig. 12. The real graph has a considerably smaller value and therefore the expected total number of 2 paths in the projection graph corresponds to the number of paths of length 2 in the bipartite graph, we define $k_{E}$.

On the other hand, we have for the probability of an edge between $P$ and $P'$ in the P-projection graph the estimate

\[ \Pr \{ P \sim P' \} = 1 - \prod_\nu \left( 1 - \frac{c_\nu^2}{N^2 \mu \nu^2} \right)^{k_{E}_\nu}. \]

and hence for the expected total number of edges $E$

\[ E \sim \sum_{\mu,\mu'} \frac{C_P^2 M^2}{(\mu \mu')^{\beta}} \left( 1 - \exp \left( - \sum_\nu \frac{C_O c_\nu^2 \mu \nu'}{C_{op} M \nu^{3-2}} \right) \right). \]
Several cases are now possible. For \( \beta > 3 \) and \( \alpha > 2 \), it is easy to see that \( \lim_{N \to \infty} \frac{E^{(P_2)}}{E} = 1 \) and higher edge multiplicities have essentially zero probability.

The situation is different if either condition is violated, since in this case \( E^{(P_2)} - E \) diverges and can become of the same order as \( E \). For instance, we obtain for \( \beta < 3, \alpha < 2 \)

\[
E^{(P_2)} - E \simeq \sum_{\mu, \mu'} \frac{C^2 \mu^2 M^2}{(\mu \mu')^{\beta - 2}} \sum_{k \geq 2} \frac{(-1)^k}{k!} \left( \frac{C^2 \mu^2 \mu' \nu}{C_\mu M^{\beta - 2}} \right)^k
\]

\[
\simeq \sum_{\mu, \mu'} \frac{\text{const} \cdot M^2}{(\mu \mu')^{\alpha - 1}} \sum_{k \geq 2} \frac{(-1)^k}{k!} \left( \frac{\text{const} \cdot \mu' \nu}{M^{\beta - 2}} \right)^k
\]

\[
\simeq \sum_{k \geq 2} \frac{\text{const} \cdot (-1)^k}{k!} M^{\beta - k + \frac{2}{\alpha} + \frac{2}{\beta} - 2}
\]

From the last formula, we see that the expected edge multiplicity \( \frac{E^{(P_2)}}{E} - 1 \) can become positive for proper choices of \( \alpha \) and \( \beta \). We show that \( \frac{E}{E^{(P_2)}} < 1 \) under the above assumptions. Since

\[
E^{(P_2)} = \sum_{\mu, \mu'} \sum_{\nu} \frac{C_{\mu} C_{\nu}^2 \mu \nu}{C_\mu (\mu \nu)^{\alpha - 1 - \beta}}
\]

\[
\simeq \text{const} \cdot M^{\alpha - 2(2 - \alpha) + 1 + \beta(3 - \beta)}
\]

\[
= \text{const} \cdot M^{\frac{2}{\alpha} + \frac{2}{\beta} - 2}
\]

and

\[
E \simeq \sum_{k \geq 1} \frac{\text{const} \cdot (-1)^{k+1}}{k!} M^{\frac{2}{\alpha} + k(\frac{2}{\alpha} + \frac{2}{\beta} - 2)}
\]

one gets

\[
\frac{E}{E^{(P_2)}} \simeq 1 - \sum_{k \geq 2} \frac{\text{const} \cdot (-1)^k}{k!} M^{\frac{2(k-1)}{\alpha} + \frac{2(k-1)}{\beta} - 2k}
\]

\[
\simeq 1 - \text{const} \cdot M^{\frac{2}{\alpha} - \frac{2}{\beta} \left( M^{\frac{2}{\alpha} + \frac{2}{\beta} - 1 + o(1)} \right)}
\]

\[
= 1 - \text{const} + o(1)
\]

Since the involved constant is positive we get the desired result. A more carefully analysis, which will be part of a forthcoming paper, shows that one also obtains a power law for the edge multiplicity, as observed in the simulations.

### C. Random intersection graphs and the “Cameo” principle

In this section, we give a possible explanation for the appearance of power laws in the size distribution. In most models of complex networks with power-law like degree distributions, one assumes a kind of preferential attachment rule as in the Albert and Barabasi model. This makes little sense in our framework. Instead we propose a rule called the “Cameo Principle” first formulated in [2].

Before giving an interpretation and motivation we briefly describe the formal setting. Assign to each project a positive \( \varphi \) distributed random variable (r.v.) \( \omega \) and to each organization a positive \( \psi \) r.v. (note that, in contrast to section \( \text{[4, 5, 8]} \), \( \varphi \) and \( \psi \) are not the size distributions). We assume \( \varphi \) and \( \psi \) to be supported on \((1, \infty)\) and monotonically decaying as \( \omega \) and \( \mu \) tend to infinity. On the bipartite graph an edge between an organization \( O \) and a project \( P \) is then formed with probability

\[
p_{o,p} := \frac{c_0}{\psi^\alpha (P)} \cdot \frac{1}{\sum_{p} \psi^{-\alpha} (P)} + \frac{c_1}{\varphi^\beta (O)} \cdot \frac{1}{\sum_{O} \varphi^{-\beta} (O)},
\]

where \( c_0 \) and \( c_1 \) are positive constants, \( \alpha, \beta \in (0, 1) \), and all edges are drawn independently of one another. We are interested in the properties of the corresponding random \( P \) and \( O \)-graphs for typical realizations of the \( \omega \) and \( \mu \).
variable. The word typical is here understood in the sense of the ergodic theorem, namely we assume \( \frac{1}{N} \sum O \varphi^{-\beta} (O) \sim \int \varphi^{1-\beta} d\varphi =: C_0^{-1} \) and \( \frac{1}{M} \sum P \psi^{-\alpha} (P) \sim \int \psi^{1-\alpha} d\psi =: C_1^{-1} \), where \( N \) and \( M \) are the cardinalities of the O- and P-partitions and \( \alpha \) and \( \beta \) are such that the integral is bounded. The above formula reduces then to

\[
p_{o,p} := \frac{c_0 \cdot C_0}{M \psi^\alpha (P)} + \frac{c_1 \cdot C_1}{N \varphi^\beta (O)}.
\]  

(39)

The expected conditional size of a vertex is then given by

\[
E (|P| \mid \psi (P)) = \frac{Nc_0 \cdot C_0}{C_1 M \cdot \psi^\alpha (P)} + c_1
\]  

and

\[
E (|O| \mid \varphi (O)) = \frac{M c_1 \cdot C_1}{C_0 N \cdot \varphi^\beta (O)} + c_0.
\]  

(41)

The interpretation behind the special form of edge probability in eq. (38) is the following. The \( \omega \) and \( \mu \) values describe a kind of attractivity property inherent to projects and organizations. Thinking in terms of a virtual project formation process the final set of organizations belonging to a project \( P \) can either join the project actively—in which case the \( \mu \) value of \( P \) is important—or the organization more passively enters the project on the request of organizations already involved—in which case the attractivity \( \omega \) of the the corresponding organization is important. The attractivity of an organization could, for instance, be related to its reputation, financial strength, or quality of earlier projects in which the organization was involved. Extrapolating from human behavior, it is not directly the \( \omega \) or \( \mu \) value which enters the pairing probability, but rather the relative frequency of the \( \omega \) or \( \mu \) values: the rarer a property, the more attractive it becomes. This is in essence the content of the “Cameo” principle.

The parameters \( \alpha \) and \( \beta \) can be seen as a kind of affinity to following the above rule; for \( \alpha, \beta \to 0 \) the rule is switched off and we recover a classical Erdős-Renyi intersection graph. In general the values of \( \alpha \) and \( \beta \) are themselves quenched random variables with their own—usually unknown—distribution. As shown in [4], only the maximal \( \alpha \) and \( \beta \) values matter for the resulting degree distribution of the graphs. We therefore restrict ourself in the following to constant values.

Since the conditional expectation of the size values (eqs. (40) and (41)) are proportional to \( \varphi^{-\beta} \) and \( \psi^{-\alpha} \), we have to estimate their induced distribution. It can be shown that \( z := \varphi^{-\beta} (\omega) \) is asymptotically distributed with density \( z^{-1 + o(1)} \) when \( \varphi (\omega) \) decays monotone and faster than any power law to zero as \( \omega \to \infty \). When \( \varphi (\omega) \) is itself a power-law distribution with exponent \( \gamma \), the resulting distribution for \( z \) will be \( z^{-1 + \frac{1}{\gamma} + o(1)} \). Therefore, the induced distribution is always a power law independent of the details of \( \varphi \). Applying this result to our model, we obtain immediately a power law distribution for the size distribution on the P- and O-graphs with exponents depending essentially only on \( \alpha \) and \( \beta \). It is not difficult to see that, due to the edge independence in the model definition, the resulting degree distributions are again of power-law type. The Cameo Ansatz hence generates in a natural way a bipartite graph, where both projections admit two of the main features of the FP-networks. Furthermore, we obtain a linear dependence of the mean triangle number \( \Delta_k \) on the degree, as in section [LV.A]

None of the models discussed in section IV can reproduce scale-free distribution of the edge multiplicity with the same low exponent as observed in each of the FP networks. It will be interesting to see whether the inclusion of memory effects like the ”My friends are your friends” principle [4] will change the picture.

V. CONCLUSIONS

In this work, we have described research collaboration networks determined from research projects funded by the European Union. The networks are large in terms of size, complexity, and economic impact. We observed numerous characteristics known from other complex networks, including scale-free degree distribution, small diameter, and high clustering. Using a random intersection-graph model, we were able to reproduce many properties of the actual networks. The empirical and theoretical investigations together shed light on the properties of these complex networks, in particular that the EU-funded R&D networks match well with typical realizations of random graph models characterized by just four parameters: the size, edge number, exponent of project-projection degree distribution, and exponent of organization-projection degree distribution.

In terms of real-world interpretation, the present analysis yields three major insights. First, based on the fact that the size distribution of projects did not change significantly between the Framework Programs, any possible changes
in project formation rules—which we do not know at this stage—did not affect the aggregate structure of the resulting research networks. Second, the fact that integration between collaborating organizations has increased over time, as measured by the average clustering coefficient, indicates that Europe has already been moving towards a more closely integrated European Research Area in the earlier Framework Programs. Finally, the fact that a sizeable number of organizations collaborate more than once in each Frame Program shows that there appears to be a kind of robust backbone structure in place, which may constitute the core of the European Research Area.

In terms of application, the present results suggest a number of extensions. First, it is essential to learn more about the properties of the vertices in our networks. To what extent can they be characterized and classified? What kind of structural patterns emerge if we add this information? Second, we need to know more about the micro-structure of the networks. In which areas are the networks highly clustered and where does this clustering come from? What kind of subgroups can be identified? Third, we need to learn more about where the observed distribution of edge multiplicity comes from. Finally, it would be desirable to explicitly include edge weights into the analysis. Presumably, actors who collaborate more frequently are more proximate to each other than actors who collaborate only once. This may significantly impact the structural features we are able to observe, as well as the conclusions we might draw concerning the link between network structure and function.

Acknowledgments

We would like to acknowledge support from the Portuguese Fundação para a Ciência e a Tecnologia (Bolsa de Investigação SFRH/BPD/9417/2002 and FEDER/POCTI-SFA-1-219), ARC systems research (W4570000294-3), and from the VW Stiftung (I/80496). We thank Ph. Blanchard and L. Streit for useful discussions and commentary. Portions of this work were done at the Vienna Thematic Institute for Complexity and Innovation, EXYSTENCE Network of Excellence: IST-2001-32802.

[1] K. Barker and H. Cameron: European Union science and technology policy, RJV collaboration and competition policy, in Y. Caloghirou, N.S. Vonortas and S. Ioannides (eds.), European Collaboration in Research and Development, Edward Elgar: Cheltenham, UK and Northampton, MA, US (2004)
[2] Ph. Blanchard, T. Krueger: The "Cameo principle" and the origin of Scale-free graphs in social networks, Journal of Statistical Physics, 114, 5-6 (2004), arXiv: cond-mat/0302611
[3] Ph. Blanchard, T. Krueger: Networks of the extreme: a search for the exceptional, to appear in “Extreme Events in Nature and Society”, The Frontier Collections, Springer (2005)
[4] Ph. Blanchard, S. Fortunato, T. Krueger: Importance of extremists for the structure of social networks, arXiv:cond-mat/0407434 (2004), Phys.Rev.E, 71, (2005)
[5] Ph. Blanchard, A. Krüger, T. Krueger, P. Martin: The Epidemics of Corruption, submitted to Phys. Rev. E, (2005), arXiv:physics/0505031
[6] Ph. Blanchard, T. Krueger, A. Ruschhaup: Small world graphs by iterated local edge formation, Phys. Rev. E, 71 (2005), arXiv: cond-mat/0304563 (2003)
[7] B. Bollobas, J. Riordan: Mathematical results on scale-free random graphs, Handbook of graphs and networks, (2003)
[8] M. Karonski, E.R. Scheinerman, K.B. Singer-Cohen: On random intersection graphs: the subgraph problem, Combinatorics, Probability and Computing, 8, (1999)
[9] Newman, M.E.J.: Scientific collaboration networks: I. Network construction and fundamental results, Physical Review E, 64 (016131), (2001)
[10] CORDIS (2004): Projects Database—Advanced and Professional Database Search, available from http://dbs.cordis.lu/cordis.cgi/EF?CALLER=EIPROF_EN_PROJ&MODE=N&LANGUAGE=EN&DATABASE=PROJ
[11] CORDIS(2002): Proposal evaluation, available from http://www.cordis.lu/fp6/management/eval/hp_evaluation.htm

Figures
FIG. 1: Distribution of project sizes.

FIG. 2: Distribution of organization sizes.
FIG. 3: Degree distribution of projects projection.

FIG. 4: Degree distribution of organizations projection.
FIG. 5: Relation between degree and number of triangles in the projects projection.

FIG. 6: Relation between degree and number of triangles in the organizations projection.
FIG. 7: Distribution of edge multiplicities in the projects projection.

FIG. 8: Distribution of edge multiplicities in the projects projection.
FIG. 9: Degree distribution for the O-graphs.

FIG. 10: Degree distribution for the P-graphs.
FIG. 11: Triangle-degree correlation for the O-graphs.

FIG. 12: Edge multiplicity for the O-graphs.

Tables

| Framework Program | budget\(^*\) | \# P | million EUR/P | \#(P >1\(^{1}\)) | \# O | million EUR/O |
|-------------------|------------|------|---------------|----------------|------|--------------|
| FP1 (1984–1988)   | 3.8        | 3283 | 1.15          | 1696           | 2500 | 1.52         |
| FP2 (1987–1991)   | 5.4        | 3885 | 1.39          | 3013           | 6135 | 0.88         |
| FP3 (1990–1994)   | 6.65       | 5294 | 1.25          | 4611           | 9615 | 0.69         |
| FP4\(^{c}\) (1994–1998) | 13.3 | 15061 (9087) | 0.88 | 11374 (8039) | 20873 | 0.64 |
a billion ECU/EUR
b projects with more than one participating organization
^R&D projects listed in parentheses. The number excludes all projects devoted to preparatory, demonstration, and training activities.

TABLE I: FP1–4 total budget and number of funded projects. The smaller average funding per project and org in FP4 is an artefact as it involves a large number of scholarships and the like, which are smaller than research projects (however, we cannot isolate the bias created).

| graph characteristic | FP1 | FP2 | FP3 | FP4 |
|----------------------|-----|-----|-----|-----|
| # vertices: N        | 2500| 6135| 9615| 20873|
| (N for larg. comp.)  | (2038)| (5875)| (8920)| (20130)|
| N outside larg. comp.| 462 | 260 | 695 | 743 |
| # edges: M           | 9557| 64300| 113693| 199965|
| (# edges M larg. comp.)| (9410)| (64162)| (113219)| (199182)|
| mean degree: d       | 7.65| 20.96| 23.65| 19.16|
| (d larg. comp.)      | (9.23)| (21.84)| (25.39)| (19.79)|
| maximal degree: d_{max} | 140 | 386 | 648 | 649 |
| mean triangles per vertex: \( \triangle \) | 22.90| 169.70| 244.91| 146.04|
| (\( \triangle \) larg. comp.) | (27.97)| (177.16)| (263.84)| (151.26)|
| maximal triangle-number | 966 | 5295 | 15128| 10730|
| cluster coefficient: \( \bar{C} \) | 0.57| 0.72| 0.72| 0.79|
| (\( \bar{C} \) larg. comp.) | (0.67)| (0.74)| (0.75)| (0.81)|
| number of components | 369 | 183 | 455 | 467 |
| diameter of largest component | 9 | 7 | 9 | 10 |
| mean path length: \( \lambda \) of l.c. | 3.70| 3.27| 3.32| 3.59|
| exponent of degree distribution | -2.1 | -2.0 | -2.0 | -2.1 |
| variance of degree exponent | 0.4 | 0.3 | 0.3 | 0.3 |
| exponent of org-size distr. | -2.1 | -1.9 | -1.7 | -1.8 |
| variance of size exponent | 0.5 | 0.3 | 0.5 | 0.3 |
| mean \# projects per org: \( \mathbb{E}(|O|) \) | 2.40| 4.87| 5.6| 6.24|
| maximal size (\text{max} \ |O|) | 130 | 82 | 138 | 172 |

TABLE II: Basic network properties of FP1–4 organizations projection.
| graph characteristic                  | FP1   | FP2   | FP3   | FP4   |
|--------------------------------------|-------|-------|-------|-------|
| # vertices: \( N \)                 | 3283  | 3884  | 3528  | 9087  |
| (\( N \) for larg. comp.)           | (2764)| (3662)| (5027)| (8566)|
| \( N \) outside larg.comp.          | 519   | 222   | 501   | 521   |
| # edges: \( M \)                    | 51217 | 94527 | 202358| 348542|
| (\( M \) for larg. comp.)           | (50940)| (94471)| (202306)| (348474)|
| mean degree: \( \bar{d} \)          | 31.20 | 48.68 | 73.20 | 76.71 |
| (\( \bar{d} \) for larg. comp.)    | (36.86)| (51.60)| (80.49)| (81.36)|
| maximal degree: \( d_{\text{max}} \) | 282   | 387   | 917   | 771   |
| mean triangles per vertex: \( \triangle \) | 774.41| 871.19| 1970.30| 2034.31|
| (\( \triangle \) for larg. comp.)  | 919.53| 923.98| 2167.05| 2158.03|
| maximal triangle-number              | 12903 | 11125 | 37247 | 41141 |
| cluster coefficient: \( C \)        | 0.67  | 0.54  | 0.44  | 0.47  |
| (\( C \) for larg. comp.)           | (0.75)| (0.57)| (0.48)| (0.50)|
| number of components                 | 369   | 183   | 455   | 467   |
| diameter of largest component        | 9     | 7     | 10    | 9     |
| mean path length: \( \lambda \)     | 3.24  | 2.80  | 2.72  | 2.80  |
| exponent of degree distribution      | (-0.8, -3.4) | (-0.7, -3.3) | (-0.6, -3.7) | (-0.3, -2.2) |
| variance of degree exponent          | (0.4, 3.6) | (0.3, 1.7) | (0.3, 1.4) | (0.2, 0.6) |
| exponent of proj-size distr.         | -3.59 | -2.9  | -3.2  | -4.1  |
| variance of size exponent            | 0.6   | 0.4   | 0.2   | 0.3   |
| mean # orgs per project: \( E(|P|) \) | 3.15  | 3.08  | 3.22  | 2.71  |
| maximal size (max \(|P|\))          | 20    | 44    | 73    | 54    |

TABLE III: Basic network properties of FP1–4 projects projection.