A Social Network Analysis
of Two European Intellectual Property Conflicts

Moses Boudourides* & Sebastian Haunss**

*University of Patras, Greece, mboudour [at] upatras.gr

**University of Konstanz, Germany, sebastian.haunss [at] uni-konstanz.de

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Abstract

In this exploratory paper we use social network analysis to reveal a number of structural aspects of the actor networks that have developed during two recent European policy conflicts about intellectual property rights. Using statistical indicators we can identify distinctive relational patterns for different actor types. Using exponential random graph models we demonstrate how the two actor networks differed in their overall structure of interaction.

Introduction

The conflict about software patents in the EU has been one of the most intense policy conflicts in Europe in the last decade. This was quite surprising as before the conflict software patents have been perceived as an arcane area of patent law that attracted the attention of only a small group of specialist lawyers. The conflict was characterized by the mobilization of collective action networks that involved actors that are usually regarded as weak or hard to mobilize: Public interest groups and small and medium-sized enterprises (Olson, 1968; Schmitter and Streeck, 1999; Smith, 2008). Unexpectedly these actors were quite successful in the conflict and, in the end, prevented the adoption of the directive.

About the same time a second IP conflict developed around the proposed EU directive on the enforcement of intellectual property rights. This time, the actor network was dominated by a more traditional player: business associations and single large firms. But again, a network of civil society organizations tried to influence the decision-making process and to prohibit the directive – this time, without much success.

The fact that both conflicts happened at roughly the same time in the same institutional framework and in the same policy field, included an important set of overlapping actors, but led to opposing policy outcomes, allows us to isolate the factors that determined success or failure of the respective actors. In this paper, we focus mainly on the structural aspects of the actor networks that developed during these conflicts.

A Brief History of the Two Conflicts

Both conflicts started in the late 1990s with the publication of a Green Paper by the European Commission (COM, 1998, 1997). In the EU decision-making process Green Papers start a process of more or less formalized and open consultations leading ultimately to the draft of a directive. In our cases the directives were decided in the co-decision procedure in which the European Parliament and the Council both have to adopt a common text before the directive comes into effect (Peterson and Bomberg, 1999, 25).

It took little over four years from the initial Green Paper to the Commission's proposal for the IP enforcement directive and another 15 months to reach a final decision. In the case of software patents it took only a little longer – four and a half years – from the Green Paper to the proposal, but another three and a half years until the proposal was finally rejected. While we witness a heated debate about the pros and cons of software patens – an issue that seemed from the outset much less controversial – we see a relatively smooth and undisturbed legislative process in the case of the IP enforcement directive where one could have expected much more conflict as the directive touches upon issues like file-sharing that have received much more public attention than the arcane issue of software patents.

In both cases, the Commission has argued in its proposals with a need to harmonize the internal European market and to comply with international treaties. Furthermore, it has claimed to strengthen the competitiveness of European industries in the world with its proposals. What the Commission did de facto was not just its aim to harmonize different national legal settings but to follow a course of augmentation of intellectual property rights.

In both cases, the Commission received strong support by industry lobby groups that represented a number of powerful key players in the respective fields. But also in both cases, business interests did not unanimously support the Commission's proposals. Major firms from the European telecommunications industry opposed the IP enforcement directive and a large number of mostly SMEs opposed the software patents directive. Civil society and consumer interest groups have mobilized against the directives in both cases. In sum the actor constellation for the two cases was as follows:

	Software Patents	**IP Enforcement**
Pro	• Commission • BSA • EPO • Patent Lawyers	• Commission • Music Industry
Contra	• FFII • NoSoftwarepatents-Campaign • some NGOs	• Some large European telecommunications firms • Some NGOs • EDRi
Undecided	• Council (majority for patentability) • Parliament • SMEs • Scientific Experts	• Council (majority for the directive) • Parliament (majority for the directive) • Scientific Experts

Data Collection

Our aim was to collect as much information as possible on the actor networks that made up the two conflicts. Because we were interested in collective action networks, we focused mainly on collaboration links between actors. The problem we faced was that not all actors involved in the conflicts were willing to disclose information about their cooperation partners mainly for two reasons:

1) even though both conflicts had come to a preliminary end, the underlying controversy about the future shape of a European IP regime was not resolved,
2) for those actors involved in routine lobbying at the European level their cooperation relationships are their social capital which they would not want to disclose.

We tried to mitigate this problem by using a triangulation approach, in which we combined data from multiple sourced into one unified data set.

The data used in this network analysis comes from five main sources:

1) One part of the research project was a political claims analysis of the newspaper articles that mentioned one or both of the conflicts. Here we analyzed all articles published in mayor quality newspapers between 1997 and 2005 in Germany, France, Great Britain and Poland (Haunss and Kohlmorgen, 2008). From this data we compiled a list of actors involved in the conflict and also extracted some information about cooperation networks that were mentioned in the press.
2) We then interviewed 22 core actors from both conflicts and asked them about their cooperation networks and about other actors involved in the conflicts.
3) Combining information from both sources we constructed an online questionnaire,[1] which we asked all actors that had been identified so far to complete. Unfortunately, the response rate was disappointing. Only 60 individuals and/or organizations completed the questionnaire.
4) We analyzed two online news sources that had in depth coverage of the conflicts (http://www.heise.de & http://www.slashdot.org).
5) We systematically collected and analyzed all documents available on the Internet that were published by actors involved in the conflicts and extracted information about cooperation relationships from these documents. Specifically, we collected data on the membership networks of the central organizations involved in the conflict.
6) And we also extracted some information about network relationships from a number of other publications (Müller, 2006; Webber and Gehlen, 2006).

In the resulting network data set, we also coded a number of attributes for each actor:

– Position in the conflict (supporting the directive, opposition, neutral/unknown),
– Organizational form (individual, firm, organization/association, institution),
– Sub-network membership (political party, membership in one of the relevant business associations, participation in one of the relevant ad-hoc networks).

[1] http://www.ipgovernance.eu/questionnaire/questionnaire.html

For the analysis in this paper, we then simplified the data in the following way. Individuals who were members of one of the relevant membership organizations were reduced to this organizations (their vertices were deleted from the dataset and their relationships were added to the respective organization), MEPs were reduced to their respective political parties, and the Commissioners as well as the staff members of the Commission were reduced to the actor "Commission."

The final dataset that was derived this way now consists of firms, organizations, institutions and of individuals without or with unknown affiliation. If multiple sources mentions collaborative relations between the same actors in different circumstances, this is reflected in the value assigned to the respective link, which reflects the strength of the cooperation.

The Two Actor Networks

Using this data, we were able to reconstruct the two distinctive actor networks of the two IP conflicts: (i) the IPRED network that developed in the conflict about the first EU directive on the enforcement of intellectual property rights, and (ii) the SWPAT network that developed in the conflict about the EU directive on the patentability of computer-implemented inventions. In each one of these two policy processes, a distinctive set of actors was involved in developing a certain pattern of relations and collaboration, and possessing a certain profile of positions with respect to the contested field of intellectual property relevant for the two EU directives.

These two actor networks are 1-mode social networks generated by two distinct patterns of collaborative relations among actors in each of them. Collaboration is considered here to be a nondirectional valued relation. Nondirectional means that it is reciprocated among collaborating actors – resulting in a symmetrical adjacency matrix (sociomatrix) and a pattern of undirected lines among vertices in the corresponding graph. Being valued means that for each pair of collaborating actors a numerical value is assigned to their link (line) that signifies the number of distinctive collaborations sustained by the pair of actors – with the result that the entries of the adjacency matrix have positive integer values representing the strength or intensity of the collaboration.

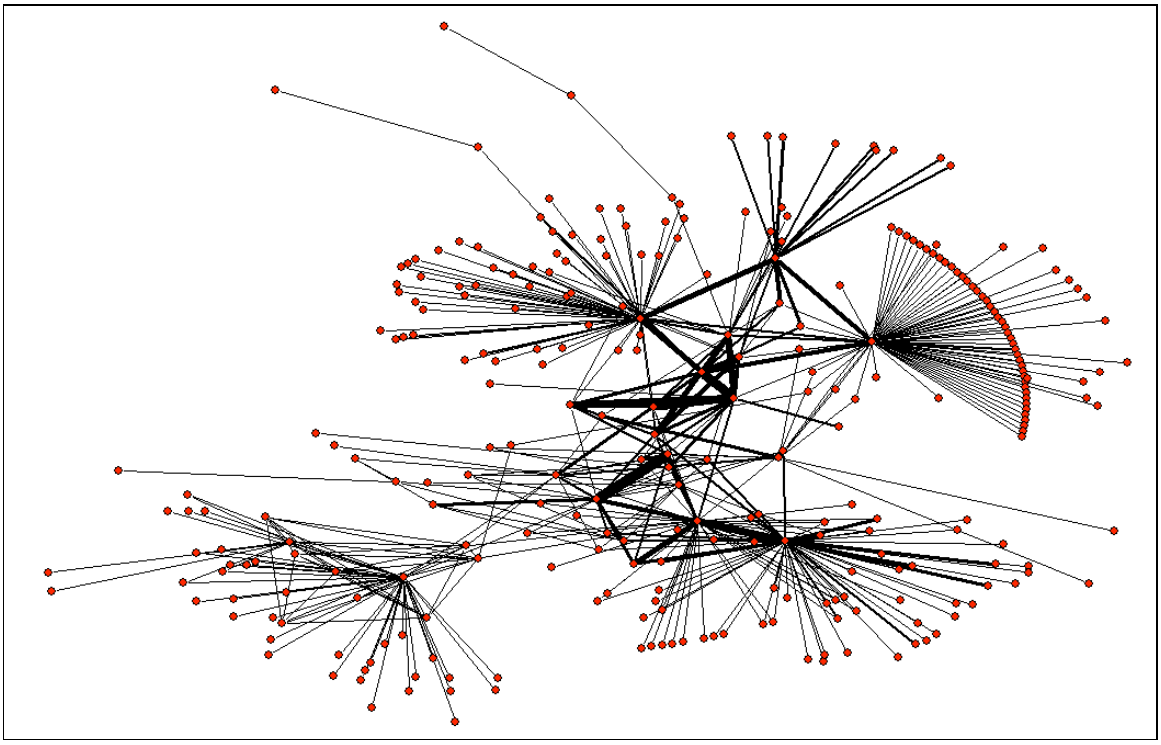

Figure 1: The IPRED network.

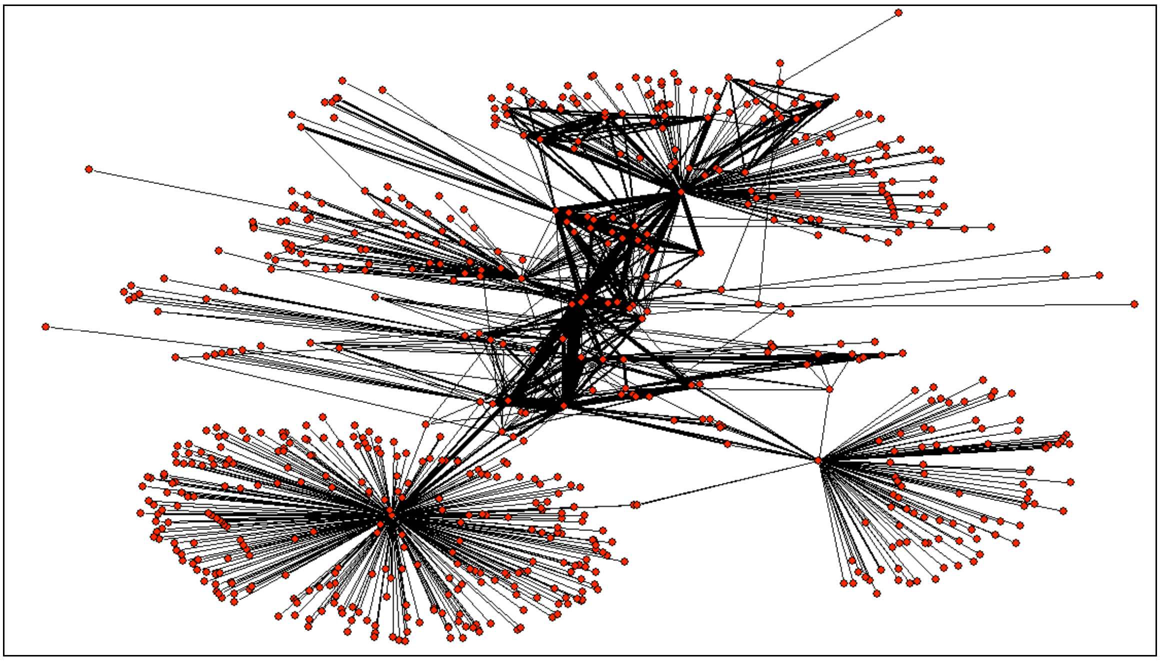

Figure 2: The SWPAT network.

Above we have drawn the two actor networks using the **Pajek** program for large network analysis. For obvious reasons, we have omitted actor labels and line values (using instead different line widths, proportional to actual line values).

In the IPRED network, there are 289 actors and 424 distinct dyads of collaborating actors. Each dyad of actors may sustain multiple collaborations – here up to a maximum of 10 (which is the value of the link between FFII and Greens EFA). Summing them up all, we find a total number of 848 dyadic collaborations. Similarly, in the SWPAT network, there are 691 actors forming 1,004 distinct dyads of multiple collaborations, where now the maximum number of collaborations in a dyad is 31 (which is the value of the link of internal collaboration in ALDE) and the total sum of collaborations over all dyads is 2,013. Figure 3 displays the distribution of the number of collaborations over dyads of actors in the two networks. Since the density of a valued network should be computed over the net number of collaborating dyads – counted once as far as a dyad might sustain at least one collaboration (this is the corresponding dichotomous relation) – the density of the IPRED network is found equal to 0.0102 and the density of the SWPAT network equal to 0.0042. Obviously, the SWPAT network is much sparser than the IPRED network.

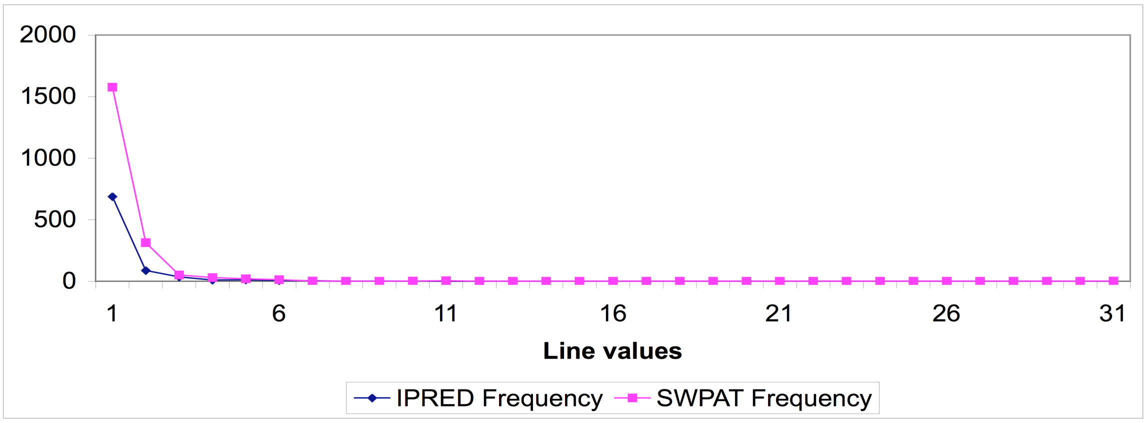

Fig. 3: Distributions of line values

Figure 4 shows, that the distribution of degrees in both networks is extremely skewed. There are no isolates. In the IPRED network 216 actors (74.74% of all actors) have the degree 1 (i.e., they have only one collaboration with another actor) and there is a single actor (0.34%) having the maximum degree of 72 – the BSA. In the SWPAT network, there are 588 actors (85.09% of all actors) with degree 1 and there is a single actor (0.14%) having the maximum degree of 293 – the EuroLinux coalition.

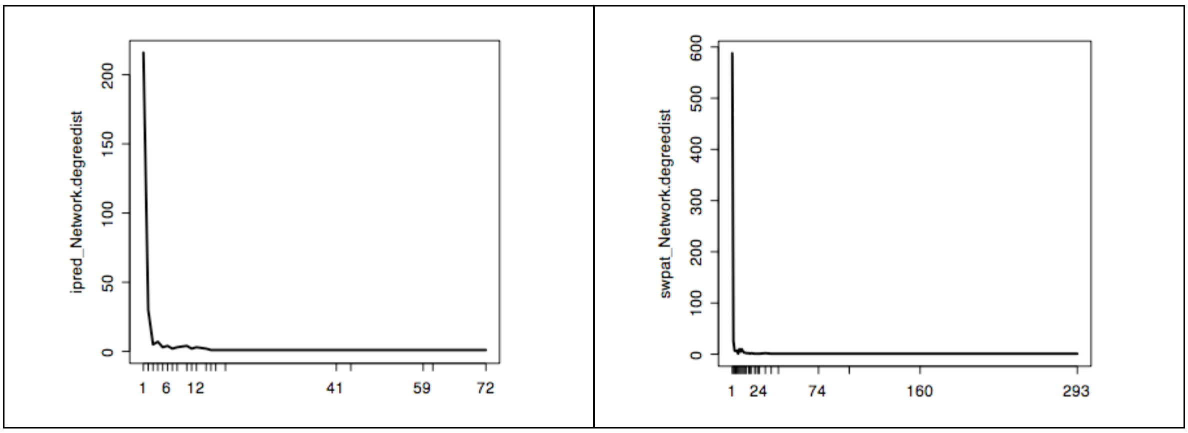

Figure 4: Degree distributions in the IPRED and the SWPAT network.

In both networks, actors are of one of the following four types: (i) individuals, (ii) members of the European Parliament (MEP) or a European Party, (iii) firms and (iv) organizations or institutions or associations. The following table gives the distribution of actor types:

	IPRED		SWPAT	
		%		%
Firms [3]	122	42.21	533	77.13
Individuals [1]	1	0.35	9	1.30
MEP/Parties [2]	6	2.08	8	1.16
Organizations [4]	160	55.36	141	20.41
Total	**289**	**100.00**	**691**	**100.00**

Table 1: Distribution of actor types [codes].

As one can see, although the majority of actors in the IPRED network consists of organizations (55.36%), the majority in the SWPAT network is firms (77.13%).

Finally, as we have mentioned above, actors may take the following positions with respect to the context of the corresponding EU directive: (i) pro, (ii) neutral and (iii) contra. The following table gives the distribution of actor positions:

	IPRED		SWPAT	
		%		%
Pro [1]	107	37.02	214	30.97
Neutral [0]	45	15.57	70	10.13
Contra [-1]	137	47.40	407	58.90
Total	**289**	**100.00**	**691**	**100.00**

Table 2: Distribution of actor positions [codes].

The majority of actors in the SWPAT network is against the EU directive, while the percentage of supporters of the directive is higher in the IPRED than in the SWPAT network (although minoritarian in both).

The following four visualizations are displaying graphically the distribution of actor types and actor positions on the graphs of the two dichotomous networks.

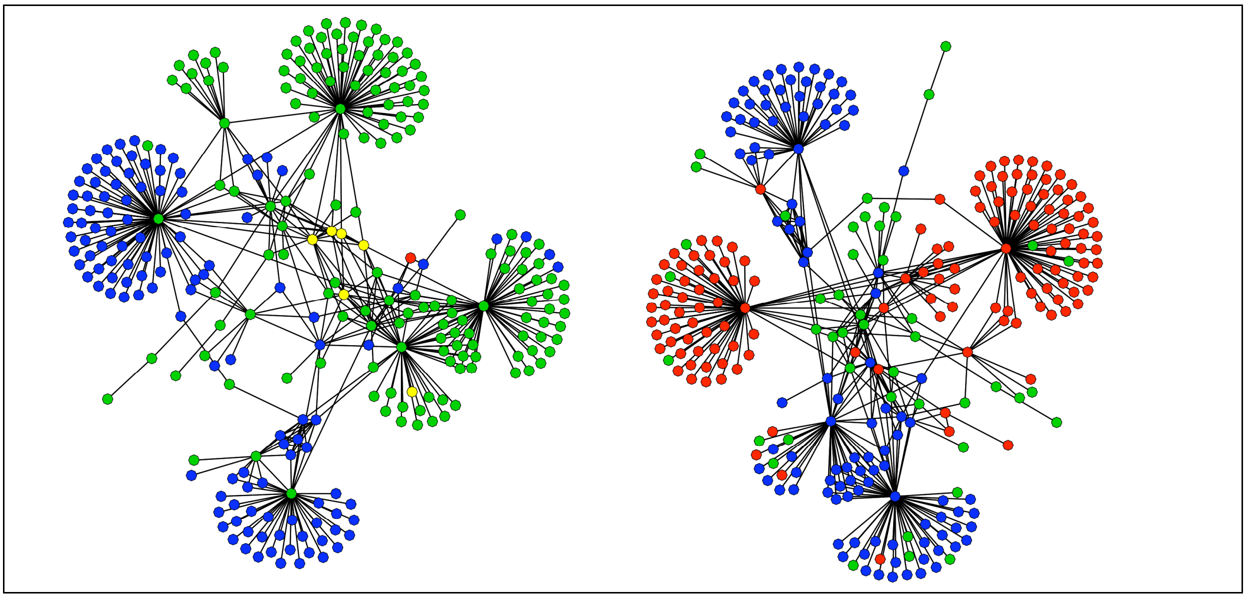

Figure 5: The dichotomous IPRED network partitioned over
Left: actor types, where firms are blue, organizations green, MEP/Parties yellow and individual(s) red
Right: actor positions, where contra is red, neutral green and pro blue.

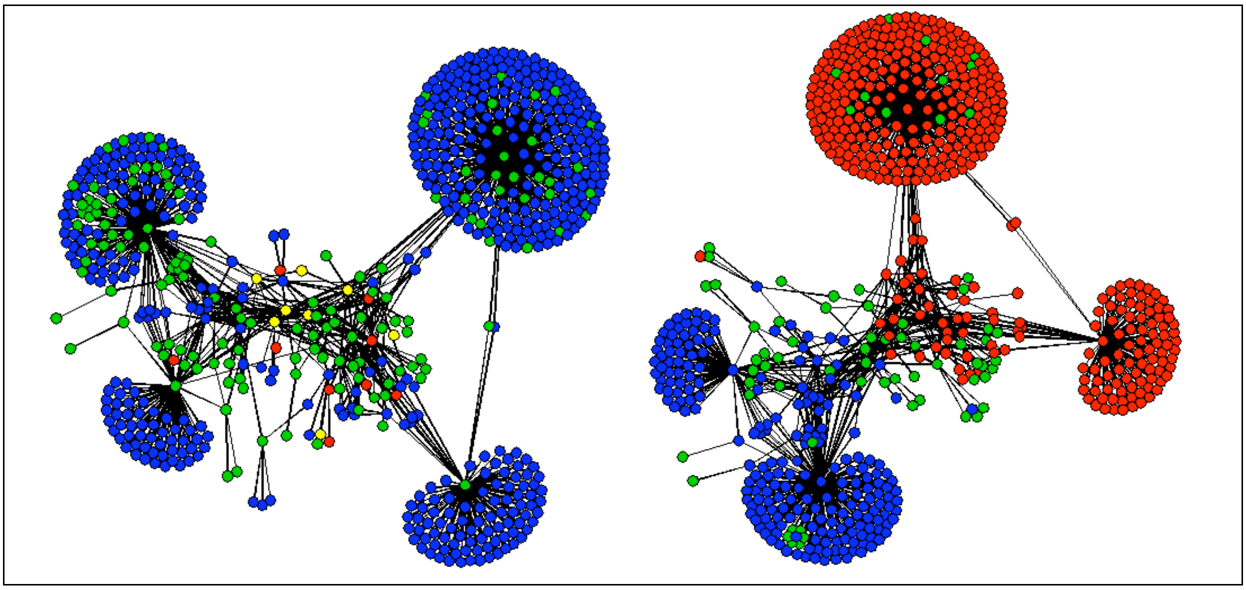

Figure 6: The dichotomous SWPAT network partitioned
Left: over actor types, where firms are blue, organizations green, MEP/Parties yellow and individuals red.
Right: over actor positions, where contra is red, neutral green and pro blue.

Structural Properties of Actors

Now, we are going to discuss a series of certain structural indicators, which may characterize how actors are embedded in their corresponding networks. Moreover, since these indicators take numerical values, it is possible to compare them and also examine whether they correlate with each other. Thus, the general idea is to determine certain structural properties that actors acquire through their interdependence with other actors in the network where they coexist and relate to each other through their actions of collaboration on the basis of their participation in the two policy processes around intellectual property issues. For this purpose, after giving a short presentation of the meaning of these structural properties, we will display the corresponding structural indicators and comment upon any interesting features we might observe.

The first actor property that we are going to examine is about the "size" of actors in our network data. But how can we measure "size" in a set of actors, who are heterogeneous ranging from individual to collective actors? One possibility would be to consider a "membership size" of actors. This measurement would create a big problem: all individual actors would possess a low "respondents' size" (equal to 1), although their contribution and embeddedness in the network might be quite important. This is why, instead of the previous "respondents' size," we prefer to use a notion of an actor's "relational size," which is defined by the number of distinct collaborations that all respondents belonging to or affiliated with that actor are reporting that they have developed with other actors in the network. We call "relational rate" or simply "rate" of an actor the ratio of the number of distinct collaborations of that actor divided by the total number of all collaborations in the survey.

Computing rates in this relational sense yields four organizations on top (CODE, BSA, IFPI, EDRi and the European Commission), while a large number of organizations are at the bottom of this ranking. However, we also obtain a very interesting result. Although the mean rates in both networks are almost 0, the distribution of rates of MEP/Parties appears to be more concentrated than in any other type of actors, as it is shown in the following two boxplots.

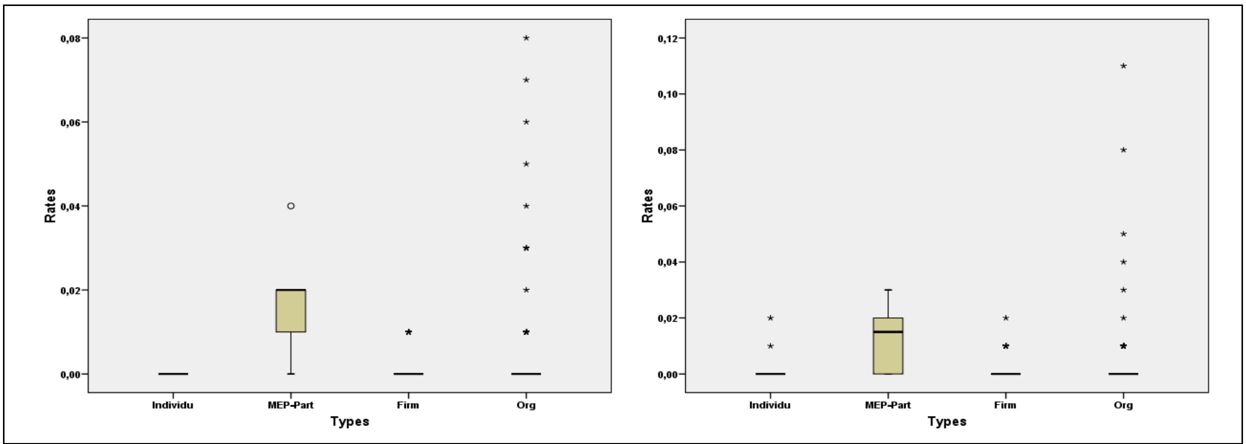

Figure 7: Boxplots of rates for actor types in the IPRED network (left) and of rates for actor types in the SWPAT network (right).

The boxplots in Figure 7 show that individuals, firms and organizations all show a similar pattern of cooperation that is: in general a very low level of cooperation. Only a small number of firms, individuals and organizations (the outliers) have higher cooperation values. These are the important actors in the conflict.

The political parties show a different pattern of cooperation, which is more homogenous. This is the result of their structurally similar position in the conflict. The political parties were the main addressees of lobbying and the political mobilizations. They had to cooperate with a number of actors and do this at similar rates. The comparatively small size of the 50% box that – in contrast to the other actor types is not zero – reflects this similar behavior, and at the same time reflects the different role the parties played in the conflicts, depending on their size and the function of certain MEPs in the relevant committees.

To qualify these findings we have computed two more relational indicators based on the pattern of collaborations that an actor might sustain. To define them, we first need to observe whether an actor's collaborations is internal (i.e., collaborations among respondents belonging to or affiliated with the same actor) or external (i.e., collaborations among respondents in different actors). Then, following Cornwell & Harrison (2004), we define the two indicators as follows: An indicator called "This/Other" is defined as the ratio of an actor's external collaborations divided by the total sum of all external collaborations in the survey. And an indicator called "Other/This" is defined as the ratio of an actor's external collaborations divided by the sum of all (internal and external) collaborations of that actor.

Ranking the indicator This/Other in descending order, we find an organization at the top, CODE, followed by the party EPP-ED, and then by four other organizations (European Commission, Anti-Piracy Coalition, FFII and EDRi), while at the very end we see a number of firms and the organization ETNO being at the very last position in this ranking. Similarly, the five top actors in the Other/This ranking are organizations (FIAPF, EFCA, ENPA, FEP and FERA/AIDAA), while again a number of Firms are at the bottom. It is still interesting, that again, for these two relational indicators, the actor type of MEP/Parties exhibits an interesting distribution, as we can see in the following two figures (for the Other/This indicator).

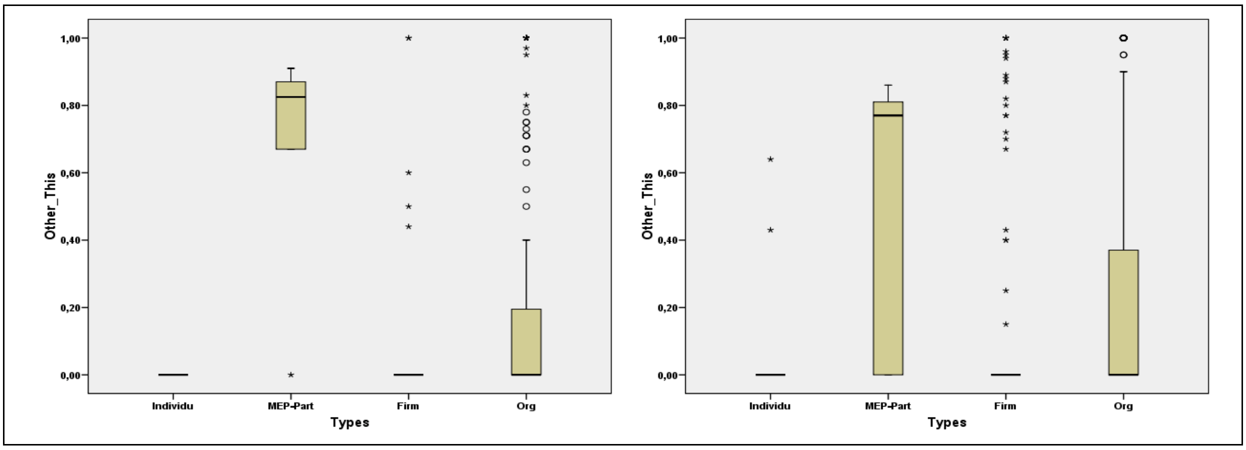

Figure 8: Boxplots of "other/this" for actor types in the IPRED network (left) and of "other/this" for actor types in the SWPAT network (right).

The Other/This boxplots (Figure 8) provide a differentiation of the findings illustrated in Figure 7: For the political parties we see a dominant pattern of outward-oriented cooperation in the IPRED case, but see a differentiation between inward and outward oriented cooperation in the SWPAT conflict. Due to the generally very low level of interaction of individuals and firms most actors again have a value of (almost) zero. The cluster of outliers of firms in the SWPAT network reflects the fact that those firms that played an active role in the conflict interacted mostly with individuals MEPs and organizations and not so much with other firms. This makes perfect sense as they tried to influence not primarily other firms but the relevant decision-makers in Europe. Organizations, on the other hand, show in both conflicts a strong tendency to interact predominantly with other organizations and institutions. This pattern reflects two aspects of the conflicts: First, the attempts of the business organizations and other collective actors to influence the commission, which was coded with the value 4 (organization/institution) in our data set. Second, this is an expression of the Brussels lobbying environment where interest groups mainly interact with each other and the European institutions an in which the European Parliament has not yet found a fixed place. In both our conflicts the established associations relied primarily on their established contacts with the commission and only relatively late realized the importance of the EP.

To complete the picture, we have also computed the four standard indicators of network centrality: degree centrality, betweenness centrality, closeness centrality and Bonacich power index (Wasserman & Faust, 1994). Let us note that the computation of the first three centrality indicators was necessarily done over the corresponding dichotomous networks. In all cases, these computations were implemented with the help of the **sna** package (Butts, 2007).

IPRED

	Mean	*Standard Deviation*	*Maximum*	*Minimum*
Rates	0	0.01	0.08	0
This/Other	0	0.01	0.1	0
Other/This	0.14	0.31	1	0
Degree Centrality	5.87	15.27	144	2
Betweenness Centrality	363.46	1723.93	16427.39	0
Closeness Centrality	0.29	0.04	0.42	0.18
Bonacich Power Index	-0.08	1	5.79	-2.84

SWPAT

	Mean	*Standard Deviation*	*Maximum*	*Minimum*
Rates	0	0.01	0.11	0
This/Other	0	0.01	0.09	0
Other/This	0.08	0.24	1	0
Degree Centrality	5.81	27.79	586	2
Betweenness Centrality	873.98	7926.34	154727.63	0
Closeness Centrality	0.28	0.03	0.46	0.2
Bonacich Power Index	-0.67	0.75	7.74	-6.18

Table 3: Statistics of the seven relational indicators.

In the ranking of degree, betweenness and closeness centralities, we obtain a similar pattern as with rates: the same two organizations are always at the top (BSA and IFPI), while there are both organizations and firms at the end in all three cases. Furthermore, in the ranking of Bonacich power index, we still see two organizations at the top (IFPM and European Commission), while organizations and firms are still at the very end of this ranking. Finally the following two tables display correlations among all seven relational indicators for the two networks.

Correlations

		Rates	This_Other	Other_This	Degree_Centrality	Betweenness_Centrality	Closeness_Centrality	Bonacich_Power_Index
Rates	Pearson Correlation	1	,824**	,320**	,932**	,884**	,614**	,050
	Sig. (2-tailed)		,000	,000	,000	,000	,000	,399
	N	289	289	289	289	289	289	289
This_Other	Pearson Correlation	,824**	1	,479**	,608**	,577**	,584**	,046
	Sig. (2-tailed)	,000		,000	,000	,000	,000	,433
	N	289	289	289	289	289	289	289
Other_This	Pearson Correlation	,320**	,479**	1	,182**	,180**	,275**	,085
	Sig. (2-tailed)	,000	,000		,002	,002	,000	,149
	N	289	289	289	289	289	289	289
Degree_Centrality	Pearson Correlation	,932**	,608**	,182**	1	,952**	,533**	-,002
	Sig. (2-tailed)	,000	,000	,002		,000	,000	,974
	N	289	289	289	289	289	289	289
Betweenness_Centrality	Pearson Correlation	,884**	,577**	,180**	,952**	1	,572**	,050
	Sig. (2-tailed)	,000	,000	,002	,000		,000	,394
	N	289	289	289	289	289	289	289
Closeness_Centrality	Pearson Correlation	,614**	,584**	,275**	,533**	,572**	1	,015
	Sig. (2-tailed)	,000	,000	,000	,000	,000		,803
	N	289	289	289	289	289	289	289
Bonacich_Power_Index	Pearson Correlation	,050	,046	,085	-,002	,050	,015	1
	Sig. (2-tailed)	,399	,433	,149	,974	,394	,803	
	N	289	289	289	289	289	289	289

**. Correlation is significant at the 0.01 level (2-tailed).

Table 4: Pearson Correlations for the IPRED indicators.

Correlations

		Rates	This_Other	Other_This	Degree_Centrality	Betweenness_Centrality	Closeness_Centrality	Bonacich_Power_Index
Rates	Pearson Correlation	1	,703**	,386**	,935**	,919**	,385**	-,009
	Sig. (2-tailed)		,000	,000	,000	,000	,000	,818
	N	691	691	691	691	691	691	691
This_Other	Pearson Correlation	,703**	1	,622**	,442**	,498**	,365**	,044
	Sig. (2-tailed)	,000		,000	,000	,000	,000	,249
	N	691	691	691	691	691	691	691
Other_This	Pearson Correlation	,386**	,622**	1	,192**	,129**	,179**	,050
	Sig. (2-tailed)	,000	,000		,000	,001	,000	,186
	N	691	691	691	691	691	691	691
Degree_Centrality	Pearson Correlation	,935**	,442**	,192**	1	,945**	,341**	-,052
	Sig. (2-tailed)	,000	,000	,000		,000	,000	,168
	N	691	691	691	691	691	691	691
Betweenness_Centrality	Pearson Correlation	,919**	,498**	,129**	,945**	1	,385**	-,045
	Sig. (2-tailed)	,000	,000	,001	,000		,000	,241
	N	691	691	691	691	691	691	691
Closeness_Centrality	Pearson Correlation	,385**	,365**	,179**	,341**	,385**	1	,025
	Sig. (2-tailed)	,000	,000	,000	,000	,000		,520
	N	691	691	691	691	691	691	691
Bonacich_Power_Index	Pearson Correlation	-,009	,044	,050	-,052	-,045	,025	1
	Sig. (2-tailed)	,818	,249	,186	,168	,241	,520	
	N	691	691	691	691	691	691	691

**. Correlation is significant at the 0.01 level (2-tailed).

Table 5: Pearson Correlations for the SWPAT indicators.

An Exponential Random Graph Model

In recent years, there has been a growing interest in exponential random graph models (ERGMs), which are often also referred as *p** models (Holland and Leinhardt, 1981; Frank and Strauss, 1986; Wasserman and Pattison, 1996; Robins, Pattison, Kalish, and Lusher, 2007). In a nutshell, the purpose of ERGMs is to describe the local relational forces that shape the global structure of a network. To this end, a network data set, like the IPRED or the SWPAT data set that we are studying here, is considered as the outcome of an unknown stochastic process or, better said, as a regression model, where the predictors are things like "propensity for actors to form dyadic links," or "propensity of actors of the same type or of the same positions to collaborate with each other" – in fact, these are the two hypotheses that we are going to test here for our networks.

To be able to give a few more technical details of how ERGMs work, let us denote by $\mathbf{Y}$ the adjacency matrix of a dichotomous network ($Y_{ij} = 1$, if an edge exists between actors i and j, and $Y_{ij} = 0$, otherwise). Implicit here is the fact that ERGMs, at the moment, work only for dichotomous nonreflexive relations (not necessarily nondirectional). Therefore, to apply them in our two case, we reduce our networks to their corresponding dichotomous networks – essentially by reducing to 1 all nonzero values of relations among actors and getting rid of all self-links (the internal collaborations of actors).

The general goal of ERGMs is to produce probabilistic models of $\mathbf{Y}$ based on the observed network data sets, since the complexity of the studied phenomena does not permit us to know the exact form of any possible stochastic process that might govern the evolution of the network. Let us denote by $\mathcal{Y}$ the set of all possible obtainable networks (with dichotomous nonreflexive relations on a fixed set of actors). In other words, $\mathcal{Y}$ is the support of $\mathbf{Y}$ and the network that we observe in reality is a single member of $\mathcal{Y}$ that we denote by $\mathbf{y}$. Of course, the whole set $\mathcal{Y}$ cannot be known in reality, but what ERGMs manages to do is to represent $\mathcal{Y}$ through simulations in a large pool of (artificial) networks and to use these simulated networks in order to conduct statistical fits, inferences and tests of hypotheses about the dominant structural features of the observed (real) network $\mathbf{y}$.

Furthermore, usually, beyond the network information contained in $\mathbf{Y}$, there are some more additional data, such as a set of measured attributes or characteristics for each actor in the network (in our case, actor types and actor positions are such given attributes). So, let us denote by $\mathbf{X}$ the matrix of all actor attributes that we happen to know.

Using this notation, the fundamental assumption in ERGMs (because of which the name "exponential random graph" is given) is that the probability of observing a particular network $\mathbf{y}$ is an exponential function of statistics that may depend on the observed network itself as well as on the attributes $\mathbf{X}$ of its actors. In a mathematical formula, this assumption is generally expressed as:

$$P_\theta(\mathbf{Y} = \mathbf{y} \mid \mathbf{X}) = (\boldsymbol{\kappa}(\boldsymbol{\theta}))^{-1} \exp\{\textstyle\sum \theta_k\, g_k(\mathbf{y},\mathbf{X})\},\ \mathbf{y} \in \mathcal{Y},$$

where $\mathbf{g}(\mathbf{y},\mathbf{X})$ is a vector of statistics derived from the observed network $\mathbf{y}$ and from the observed attributes $\mathbf{X}$ and the vector $\boldsymbol{\theta}$ denotes the statistical parameters governing the probabilistic formation of the network. The denominator $\boldsymbol{\kappa}(\boldsymbol{\theta})$ is a normalizing constant that ensures that the above expression defines a probability (i.e., the sum over all possible $\mathbf{y}$ equals 1). Moreover, we need to say that in the above formula we have suppressed the dependence of the probability $P_\theta(\mathbf{Y} = \mathbf{y} \mid \mathbf{X})$ on $\mathcal{Y}$ and we need also to add that the support set $\mathcal{Y}$ should be specified in such a way that all its elements might share the same structural and attributional characteristics with the particular distribution of the observed attributes **X** on the observed network **y**.

Equivalently, the above assumption can be formulated in terms of the log-odds that any given edge (collaboration, in our case) will exist given the observed network **y** and the attributes **X** of its actors:

$$\text{logit}\,(Y_{ij} = 1) = \sum \theta_k\, \delta_k^{ij}\,[\mathbf{g},\mathbf{y},\mathbf{X}],$$

where $Y_{ij} = 1$ signifies the occurrence of an actor pair in **Y** and $\boldsymbol{\delta}^{ij}\,[\mathbf{g},\mathbf{y},\mathbf{X}]$ is the change in $\mathbf{g}(\mathbf{y},\mathbf{X})$, when the value of y_{ij} is toggled from 0 to 1.

Now, applying this statistical methodology to our network data, we are going to consider an ERGM model that includes the edge (collaborations) count $L(\mathbf{y})$ (on the observed network **y**) along with the count of matched actor types $S_{\text{types}}(\mathbf{y},\mathbf{X})$ and matched actor positions $S_{\text{positions}}(\mathbf{y},\mathbf{X})$ on dyads of linked (collaborating) actors (according to the observed attributes **X**):

$$P_{\theta,\zeta,\eta}\,(\mathbf{Y} = \mathbf{y} \mid \mathbf{X}) = (\boldsymbol{\kappa}(\theta,\zeta,\eta))^{-1} \exp\{\theta\, L(\mathbf{y}) + \zeta\, S_{\text{types}}(\mathbf{y},\mathbf{X}) + \eta\, S_{\text{positions}}(\mathbf{y},\mathbf{X})\},$$

where θ, ζ and η are the statistical parameters of the model. Apparently, we might say that the aim of this model is to estimate statistically the overall effect of the number of edges (collaborations) together with two types of homophily/heterophily effects, one in actor types and another one in actor positions. The model fit was implemented with the package **statnet** (Handcock *et al.*, 2003), which is based on the R statistical environment (R Development Core Team, 2007). The outcomes of the model fit are given in the following table:

	IPRED network		SWPAT network	
Parameters	**Estimate**	**Standard Error**	**Estimate**	**Standard Error**
Edges-collaboration (θ)	-5.529	0.107***	-5.939	0.075***
Homophily in actor types (ζ)	0.297	0.099 **	-1.916	0.072***
Homophily in actor positions (η)	1.436	0.109***	2.050	0.083***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 6: ERGM parameter estimates for the IPRED and the SWPAT networks.

To interpret the above estimated coefficients, first we get (Goodreau *et al.*, 2008):

- θ = log-odds of completely heterogeneous (heterophilic) edges/collaborations (both in actor types and positions),
- $\theta_1 = \theta + \zeta$ = log-odds of partially homogeneous (homophilic) edges/collaborations only in actor types,
- $\theta_2 = \theta + \eta$ = log-odds of partially homogeneous (homophilic) edges/collaborations only in actor positions,
- $\theta_3 = \theta + \zeta + \eta$ = log-odds of completely homogeneous (homophilic) edges/collaborations (in either actor types or positions).

Next, we derive the probabilities corresponding to these log-odds according to the formula:

probability = (exp(log-odds)) / (1 + exp(log-odds)),

in order to get the following probabilities:

	IPRED network	**SWPAT network**
	Probability	**Probability**
Completely heterogeneous (heterophilic) edges/collaborations	0.0040	0.0026
Homogeneous (homophilic) edges/collaborations in actor types	0.0053	0.0004
Homogeneous (homophilic) edges/collaborations in actor positions	0.0164	0.0201
Completely homogeneous (homophilic) edges/collaborations	0.0220	0.0030

Table 7: ERGM computed probabilities of various types of homophilic or heterophilic edges/collaborations in the IPRED and SWPAT Networks.

From the above table, we see that, according to the ERGM fits, in the dynamics of the IPRED network, the most probable outcome is complete homophily and the least probable outcome is complete heterophily. On the other hand, in the SWPAT network, the most probable outcome is partial homophily in actor positions and the least probable outcome is partial homophily in actor types.

These results reflect an important structural difference of both actor networks. In the IPRED conflict the main actors were business associations and civil society organizations. Only a small number of mostly large single firms tried to influence the decision-making process – without much success. The civil society actors were not able to mobilize a diverse constituency and mostly formed coalitions with other civil society organizations. The proponents of the directive relied strongly on their well-established contacts with the Commission, making their interest heard already in the drafting phase of the directive. The dominant pattern therefore was cooperation among organizations. In the European Parliament the decision-making process was relatively smooth. Differences between the three larges parties EPP-ED, PSE, and ALDE were mostly eliminated before the first reading in informal meetings. The dominant pattern here, again, is cooperation among the parties.

In the software patents conflict the picture was quite different. The actor network has a large periphery where the dominant pattern was cooperation between firms and organizations. But in the core of the network, where most interaction took place, the dominant pattern was interaction between different types of actors, especially between organizations, firms and MEPs/political parties. The factor that decides here about cooperation was not so much the organizational characteristics of the actor, but its centrality in the conflict. The result also reflects the relative autonomy of the various interest groups involved in the conflict. The opponent of software patents formed a number of independent mobilization networks that cooperated mostly though individuals and firms but usually not directly. On the side of the supporters of the directive, two business organizations, BSA and EICTA, both mobilized for the directive but again did only cooperate indirectly though firms that were members of both organizations. Their latent concurrence about which of the two would be the real representative of the IT industry did not promote close and direct cooperation.

Conclusions

In this exploratory paper, we have analyzed the structural aspects of the networks of interaction that had developed during two policy conflicts about intellectual property rights in Europe. We were interested not so much on the concrete interaction of different actors and in the role single actors have played in these conflicts, but in the structural characteristics of the two collective action networks.

Our first approach, using statistical indicators, reveals that in both networks we can see distinct patterns of collaboration depending on the actor type. Individuals, firms, organizations, and political parties show different dominant patterns of interaction that exhibit some continuity over the conflicts. This supports the notion that certain attributes of an actor shape its role and pattern of interaction in a political conflict. But our analysis also suggests that actors with certain attributes have certain corridor of possibilities, in which not only single actors can vary their patterns of interaction, but which is itself structured by the overall setup of the conflict.

Using exponential random graph models our results show that these general structural characteristics of the two conflicts exhibit significant differences. The IPRED conflict was much more a traditional lobbying conflict, in which organizational actors occupied the central positions and dominated the interaction. In the SWPAT conflict, our analysis points to predominantly heterogeneous patterns of interaction, that characterize political conflicts in which various types of actors interact on multiple levels, and in which the relative centrality of an actor in the collective action network is more important as a predictor of interaction than its attributes.

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