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School bullying and social networks

Master thesis

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Abstract

Although school bullying has enormous health, social, and economic consequences that last throughout the entire human life, most bullying-prevention programs are ineffective partially because detecting bullies and their victims is challenging. This study proposes to employ social networks to identify the victims of bullying. To that aim, we elicit friendship and enmity networks and document who suffers bullying in several secondary schools in southern Spain. We show that both friendship- and enmity-network measures are relevant and complementary predictors of victimization, independent of classic non-network characteristics employed in the literature. However, how individual positioning and global features of the social organization determine who suffers bullying differs across male and female adolescents. We discuss our results in relation to existing theories of bullying victimization in psychology and sociology.

Keywords: Aggression, social networks, school bullying, victimization, friendship, enmity, gender.

1 Introduction

Human behavior must be understood in terms of social contexts and groups to which people belong (Moreno, 1934). Not surprisingly, social conditions in childhood and adolescence shape human development. Indeed, there is large evidence that children with positive relationships with their peers have higher levels of emotional well-being, participation, and academic achievement (Wentzel, 2017). In contrast, negative relationships in childhood have adverse effects on many facets of one's life (Farrington, 1989; Peets et al., 2007; Potirniche and Enache, 2014). Furthermore, such impact on childhood and adolescence peer relationships increases over time (Kaess, 2018).

One of the most serious socialization problems in schools is bullying (Olweus, 2013; Juvonen and Graham, 2014). School bullying is defined as repeated and disruptive behavior where one or several classmates intentionally annoy or hurt other classmates, both physically and emotionally. It can take various forms, including physical assault, shoves, teasing, making threats, name-calling, or humiliation (Çalışkan et al., 2019).

School bullying is a persistent worldwide phenomenon (UNICEF, 2018; WHO, 2013) and its consequences extend to all domains of bullies' and victims' life and span throughout the whole life. More directly, bullying correlates to depression, suicidal and criminal tendencies, drug abuse and violence in both childhood and adulthood (Bernstein and Watson, 1997). However, bullying also has less direct consequences. Individuals involved in bullying have lower education and financial skills (Zych et al., 2015) and higher unemployment rates, lower wealth and income later in life (e.g. Hong and Espelage (2012); Takizawa et al. (2014); Wolke and Lereya (2015); Brimblecombe et al. (2018); Carrell et al. (2018); Sarzosa and Urzúa (2021)).

Although bullying is an understudied topic in economics,[1] this phenomenon and its consequences have stimulated large literature in other fields. They are of great concern among policymakers (Ortega Ruiz et al., 2013; Baldry and Farrington, 2007; Huang et al., 2019; Olweus and Limber, 2010; Menesini and Salmivalli, 2017; Rigby, 2002).[2] Motivated by the literature, a considerable number of bullying-prevention programs targeting group-level behavior have been designed and implemented all around the World (see Salmivalli (2010) for a review). However, the meta-analytic studies has concluded that these programs are ineffective (Smith et al., 2004; Merrell et al., 2008; Ttofi and Farrington, 2011; Gaffney et al., 2019; Ferguson et al., 2007). The disappointing results of the existing bullying prevention programs generate several questions.

In this study, we answer some of these questions. In particular, we first ask whether victimization is related more to positive or negative relationships or whether positive and negative relationships are two independent predictors of bullying. Second, is bullying a group-wide phenomenon indeed, as suggested by the literature in sociology, or is it only related to local networks, without any relation to more distant network neighborhoods? Lastly, since bullying is a gender-specific phenomenon (Maccoby and Jacklin, 1980; Olweus, 1991; Carbone-Lopez et al., 2010; Silva et al., 2013; Sentse et al., 2015), we pay particular attention to whether how social organization relates to victimization differs across genders.

To answer these questions, we exploit the tools of network theory, linking bullying victimization and the patterns of social interactions. To these aims, we first elicit a large dataset on 3,035 students in 11 high schools in Andalusia, the most populated region in Spain. Notably, the data contain an enormous amount of information about all the students, their classes, and schools, including the friendship and enmity networks and self- and other-reported bullying victimization (see Section 3 for details). In our analysis, we explore to what extent the friendship

[1] See e.g. Brown and Taylor (2008) or Sarzosa and Urzúa (2021) for exceptions.

[2] *Stop bullying* (www.stopbullying.gov) and *Beat Bullying* (www.coe.int/en/web/edc/beat-bullying) are examples of public programs documenting and targeting bullying in the US and European Union, respectively.

and/or enmity network information at different levels predict the likelihood of becoming a victim of bullying.

Our results indicate that victims occupy peripheral positions in the class friendship networks. However, they are more central in the enmity networks both locally using local measures of centrality and globally using global measures of one's centrality.[3] Moreover, both types of relationships are independent predictors of victimization. Network-wide characteristics of the class networks also play a role while explaining victimization, but their impact is quantitatively weaker than that of individual positioning, contradicting the classic approaches to bullying prevention that exclusively target groups rather than individuals. However, since both levels matter differently, the existing programs should target both groups and individuals. Moreover, the positioning of male and female victims differ considerably, suggesting that the reasons why each gender is victimized are different.

To the best of our knowledge, the only paper that relates bullying networks is Mouttapa et al. (2004). They analyze a sample of predominantly Latino and Asian schools in the U.S. and correlate bullying with certain features of students' local networks, such as the number of friends and the likelihood of people having friends engaged in bullying. They find that victims receive fewer friendship nominations from others, but this effect only holds for women. As opposed to Mouttapa et al. (2004), our sample is more extensive and dramatically more representative of the general school population. In addition, we combine both friendship and enmity networks, and our data–particularly the high number of independent networks in our sample–allow us to analyze the role of (not only students' direct network neighborhoods but also) the entire network architecture in the school. Therefore, our results largely extend their work, provide a more general picture of the role of social organization in bullying, and provide different policy recommendations.

The remainder of the paper is structured as follows. Section 2 reviews the literature and presents our research hypotheses. In Section 3, we describe our methodology and the data. Section 4 presents the results. Finally, the last section concludes.

2 Related literature and research hypotheses

Our starting hypothesis is that, since bullying is by definition a social phenomenon, the structure of the social organization in schools can stimulate or mitigate bullying. However, the open question is which particular features of social organization matter and how. In this section, we generate several research hypotheses based on the existing theories of bullying victimization in psychology and sociology. To achieve these aims, we focus on analyzing the interaction patterns among peers at school using network data. Social network analysis is a suitable approach to studying links between nodes, how they are connected by existing friendship or enmity, or they are isolated due to lack of these links (Borgatti

[3]See Section 3 for the different measures employed in this study.

et al., 2018; Wasserman et al., 1994).

We first discuss whether bullying is a local or group-level phenomenon. Although the literature considers different levels within the socio-cultural structure (Hinde and Stevenson-Hinde, 1987), currently, the dominant theory in the literature that motivates most of the interventions is that bullying is a group-level phenomenon (O'connell et al., 1999; Oldenburg et al., 2018; Lagerspetz et al., 1982; Sutton and Smith, 1999).

Therefore, if the group-level norms and organization matter, then network theory predicts that network-wide characteristics (rather than individual positioning) predict the extent of victimization. Hence, we hypothesize the following:

H_1 Global-wide network characteristics predict the extent of bullying victimization.

However, the literature does not provide any specific theory regarding which characteristics determine bullying and in which direction. Hence, rather than generating our specific hypotheses, we let the data speak and explore the natural candidates postulated by network theory, such as measures of integration, connectivity, and hierarchy (see Section 3).

In contrast to the current theories, the earlier literature has mostly focused on identifying individual risk factors (Juvonen and Graham, 2001, 2014) and the determinants of victimization (Graham, 2016; Olweus, 1997). Hence, we also correlate victimization with individual positioning in friendship and enmity networks.

As for friendship networks, Haynie et al. (2001) state that victims exhibit lower self-esteem, feel lonelier, and are less happy at school than their peers. At the same time, it has also been shown that conflict can be reduced with the social influence of referring students and that friendships can provide protection against victimization (Paluck et al., 2016; Paluck and Shepherd, 2012). These claims suggest that victims should have fewer friends or, in network terminology, should have lower connectivity and degree in the friendship networks. In contrast to these claims, Mouttapa et al. (2004) do not find correlations between the number of friends and victimization though.

Our second hypothesis is:

H_2 Connectivity/degree in the friendship networks is negatively related to victimization.

The role of connectivity (i.e. local centrality) notwithstanding, there are neither theories nor empirical evidence regarding the role of whether the victims would be less central globally. Since our network approach allows us to compute global centrality measures (see Section 3), we test whether being globally central– on top of having many friends–plays a role in victimization but we provide no research hypothesis in this respect.

As discussed above, negative interactions might also matter. Moreover, since bullying is a negative social phenomenon by definition, enmity interactions might, in fact, be more important predictors than friendships. It has been documented that negative peer attitudes and hostile school environmental factors can increase the frequency of bullying (Meyer-Adams and Conner, 2008; Pellegrini and Bartini, 2000; Totura et al., 2009; Hong and Espelage, 2012; Rigby, 2005). Therefore, we test whether having many enemies (that is, high local centrality in the enmity network) predict bullying victimization, using the following hypothesis:

H_3 High connectivity in enmity networks predicts bullying victimization.

Once again, we have no hypothesis regarding whether less local measures of positioning in the enmity networks matter and how.

Finally, there is extensive evidence that bullying is a gender-specific phenomenon in determinants and forms. Girls tend to engage in more indirect bullying (such as gossiping) while boys are more direct (e.g., aggression) (Farrington and Baldry, 2010; Olweus, 1991; Scheithauer et al., 2006; Borg, 1999). Boys are more likely to be involved in bullying than girls, although this effect is less robust across studies (Markkanen et al., 2021). In addition, almost all results in Mouttapa et al. (2004) are gender-specific. Therefore, we hypothesize that:

H_4 Social network positioning and global structure of the class friendship and enmity networks determine bullying victimization differently across genders.

Apart from the hypotheses stated above, we test other issues that are not supported or discussed in the literature but which we find of practical relevance. For example, will the local positioning be more, equally, or less important than the network-wide patterns? Is the role of positive and negative relationships complementary predictors of bullying, or do they provide the same information about bullying? These questions are relevant because practical applications of our results should potentially elicit the whole network architectures and both negative and positive relationships. That would require data collection and work that is more complex than eliciting and employing simple individual characteristics.

3 Data and methodology

The data for this project have been collected by the authors as a part of the *COMPHAS* project.[4] We collected a sample of schools in southern Spain, in which we conducted an extensive in-class survey with 1^{st} - 4^{th} grade students. The survey

[4]The project called *Mapeo de Competencias y Habilidades del Alumnado de Enseñanza Secundaria* is managed by the Loyola Behavioral LAB (a behavioral economics research center) and the ETEA Foundation at the Universidad Loyola Andalucía. The project was positively evaluated by the Ethics Committee of the Universidad Loyola Andalucía.

was computerized using an online platform Sand (https://sand.kampal.com), designed for the elicitation of network (and other) data. The survey was conducted between 2021 and 2022 in 11 secondary schools in Andalusia, Spain. All students in the sampled schools were contacted and invited to carry out the survey. Out of the 3,035 students officially enrolled in the schools, 2,521 agreed to start the experiment. We found absenteeism cases, and some students did not finish the online survey. A total of 2,401 students completed the entire survey. In this final sample, 1,210 were men, 1,157 women, 21 reported non-binary gender, and the rest did not answer the gender question. A fraction of 7.4% of students are of migrant origin; this figure is slightly lower than the average of 9.9% in the Spanish non-University education system.

The scope of the survey was broad and not only oriented toward the goal of the present study. We elicited a large battery of students' skills, abilities, behaviors, and attitudes. The survey was designed to provide data on various aspects that play a central role in an adolescent's daily life. The first part focuses on the sociodemographic characteristics of the school. Additionally, we elicit students' school achievement, performed risk, and time decision-making tasks, financial literacy, and cognitive reflection tests, etc. Moreover, we elicited students' self-esteem and personal satisfaction.

Importantly, the survey also included questions regarding subjects' relationships with other students in their school. This included friends and, out of the friends, the best friends, as well as enemies and, out of the enemies, the worst enemies. For that purpose, the appication provided all students with list of all the other students from the same school and year. Hence, each network in our data corresponds to all students from different classes but the same year in one school.

Last, participants indicated in the list of other students those who suffered bullying. They were explicitly stated that if they suffered it themselves, they should mark their own name, and if they knew about any other students who suffered bullying, they should mark them. Below, we term self-reported bullying the case when a student included herself in the list of bullied people in the school and other-reported bullying when others indicated someone as a victim.

From the friendship and enmity lists, we constructed the networks using the R software and analyzed them. The network data will serve as our primary explanatory variables in Section 4.

We performed a nonlinear regression analysis with the statistical package Stata. Our models correlate friendship and enmity network measures with different variables on bullying victimization (see below).

3.1 Dependent variables

Our dependent variable reflects whether an individual suffers bullying or not. During the elicitation stage, the survey explicitly included a definition of bullying, complying with the guidelines of the Ethics committee and the Spanish laws. More precisely, the students have been provided with the following information:

> ”Bullying exists when, repeatedly, several students intentionally annoy a classmate who is unable to stop it. The annoyance can be one or more of the following acts:
>
> - Teasing, insults, badmouthing, rejection, negative comments and humiliation (which can also be cyberbullying through Facebook, Whatsapp, Twitter, etc.)
>
> - Threats, hits, shoves and the like.
>
> If there is bullying in your class group, mark those who are bullied (max. 3). If they do it to you, mark yourself. If there is no bullying, don't mark anyone.”

As mentioned above, apart from this information, the program SAND has provided all students with a list of all the people in the same year in their school, including themselves. They were simply asked to mark those who suffered bullying, including themselves if that was the case according to their opinion.

From the reported data, we can distinguish two binary variables indicating whether a student is a victim or not. Firstly, self-reported bullying is the case when a student names himself as a victim, while other-reported bullying refers to cases when a student is named by another as a victim. Both variables take the value of 1 (0) if the participant is (not) a victim. Table 1 summarizes these variables on aggregate and by gender. Although females are more likely to self-report, males are more likely to be named by their peers. In addition, we employ a categorical variable measuring the number of times other classmates have mentioned a student as a victim (labeled *No. mentions* below). This variable ranges 0 to 8 in our data.

Table 1: Fractions of self-reported and other-reported bullying, disaggregated by gender

	Total		Males		Females		Others	
	N	M	N	M	N	M	N	M
Self victim-bullying	2,518	0.029	1209	0.026	1157	0.035	152	0.013
Others victim-bullying	3,029	0.094	1210	0.125	1157	0.067	662	0.083

In addition to these variables, we also analyze two other measures, which we label as “intersection” and “union” of self- and other-reported bullying. More precisely, a student is considered bullied using the intersection variable if she self-report herself as a victim *and* at least one other individual corroborates it. A student is considered a victim under the union variable if she self-reports herself as a victim *or* at least one other individual reports that she suffers bullying. Table 2 provides the number of cases in each of the four situations generated by such classification.

Table 2: Number of cases of bullying victimization in function of who reports that a students suffer bullying.

	No others-reported	Yes others-reported	Total
No self-reported	2,237	207	2,244
Yes self-reported	38	36	74
Total	2,269	241	2,518

In total, 2,518 participants answered the question about bullying, among whom 315 individuals are marked either by themselves or by others as bullying victims, representing roughly 12% of the sample. Only 74 (2.9%) students self-reported as victims of bullying, while 241 (9,4%) were reported as victims by other classmates. Their peers corroborate almost 50% of the self-reported cases. These cases correspond to our intersection variable. In contrast, 14% of other reports are corroborated by the victim.

In order to analyze the role of the entire network architecture, we consider dependent variables that add up to the victims of bullying in each network. Again we can consider the variables "intersection" and "union" of self- and other-reported bullying. However, of the 30 networks obtained[5] only 1 does not contain any type of bullying case, as Table 3 shows. Therefore, we focus on the intersection variable for greater reliability. This dependent variable is used in the Section 4.2.2. It counts the cases of bullying reported by the victims and confirmed by their peers in each network.

Table 3: Number of networks by classification based on who reports the victim of bullying

	No others-reported	Yes others-reported	Total
No self-reported	1	2	3
Yes self-reported	0	27	27
Total	1	29	30

3.2 Network variables

3.2.1 Individual positioning

The networks were elicited separately for each school-year unit. That is, each network contains people from classes corresponding to the same year in our school. We constructed four different networks from our data: friendship, best-friendship, enmity, and worst-enmity networks (see Section 4.1 for their characteristics). Therefore, each participant has four values for each individual network measure.

[5]See Section 3.2.2 for networks obtained

In the following, we introduce the network measures under study one by one:

I Centrality measures
Degree: the number of connections to other individuals independently of the direction of the link and of whether the link reciprocated or not. More due to the directions of the links, we distinguish between the following two variations of degree:

  - *Out degree*: number of nominations a student sends to his peers.
  - *In degree*: number of nominations a student receives from his peers.

Since degree is solely computed using the direct neighbors of an individual, the degree measures reflect one's local centrality. In contrast, the following three measures require knowledge of the whole network beyond one's neighborhood. Therefore, they reflect how central an individual is global:
Betweenness centrality: number of times a node is an intermediary between the pairs of other members of the network.[6] This measure reflects whether an individual is an important intermediate or broker in the class network.
Closeness: measures how close a node is to every other node in the network on average.
Eigenvector: measures the influence of a node taking into account the number of links it has with other nodes in the network and the connectivity of her network connections.[7]

II *Clustering*: a measure of the cohesion or density of one's neighborhood, computed as the proportion of neighbors of a node who are also mutual.

III *Reciprocity*: proportion of named friends/enemies by an individual that has been reciprocated by the named friends/enemies.

IV The attributes of named friends/enemies:
(Best) Friends' victimization: the fraction of (best) friends who are victims of bullying.
(Worst) Enemies' victimization: the fractions of (worst) enemies who are victims.

Table 4 summarizes all the above measures in our data. In order to differentiate between the friendship and enmity networks, we label each variable using a (+) sign if the measure was computed using the friendship networks and (-) for the enmity networks.

In addition, we also report the statistic disaggregated by gender in Table 4 to see whether there are any differences in positioning. Students who reported not

[6]See e.g. Jackson et al. (2017).
[7]See e.g. Jackson et al. (2017).

being binary and those who did not reply to the gender questions are reported jointly as "Others" in the table. We observe that males mention more friends, while females mention more enemies. Men receive more friendship nominations, but there is no significant difference in the enemy nominations across genders.

Table 4: Summary statistics of measures of individual positioning in the friendship (+) and enmity (-) networks (pooled and disaggregated by gender).

	Total (N=3,035)		Males (N=1,210)		Females (N=1,157)		Others (N=668)	
	M	SD	M	SD	M	SD	M	SD
Out degree (+)	11.79	12.053	15.82	12.903	12.742	10.470	2.843	7.603
Out degree (-)	4.393	9.536	4.636	9.976	6.1	10.801	0.997	3.791
In degree (+)	11.79	6.521	13.261	6.694	11.908	5.955	8.922	6.213
In degree (-)	4.393	4.061	4.133	3.843	4.985	4.480	3.838	3.526
Betweenness (+)	141.999	233.387	188.197	270.929	151.971	217.928	41.043	134.742
Betweenness (-)	146.495	422.562	139.037	385.862	218.769	528.248	34.822	192.516
Closeness (+)	0.008	0.065	0.010	0.062	0.012	0.082	0.002	0.019
Closeness (-)	0.048	0.189	0.060	0.207	0.055	0.201	0.015	0.112
Eigenvector (+)	0.023	0.104	0.038	0.137	0.021	0.088	0.004	0.032
Eigenvector (-)	0.013	0.0683	0.015	0.069	0.014	0.079	0.006	0.04
Clustering (+)	0.492	0.198	0.485	0.175	0.5	0.179	0.491	0.26
Clustering (-)	0.272	0.264	0.282	0.269	0.267	0.235	0.26	0.302
Reciprocity (+)	0.596	0.309	0.493	0.269	0.533	0.273	0.892	0.243
Reciprocity (-)	0.482	0.455	0.398	0.443	0.349	0.408	0.865	0.327
Victims Friend (+)	0.068	0.118	0.089	0.124	0.075	0.127	0.018	0.064
Victims Enemy (-)	0.128	0.247	0.171	0.291	0.138	0.231	0.035	0.144

3.2.2 Network-wide characteristics

As explained above, each network is constructed for all students from the same year and school. This results in 30 different networks in our data, for which we can obtain the global measures and exploit the variation across networks in our analysis.

Among the network-wide or global variables, we focus on those frequently employed in the literature (see Jackson (2011)). Table 5 provides a summary of the basic statistics of the global measures considered in our analysis for the positive and negative networks.

We first consider the number of nodes (i.e. the total number of students) and the number of edges (i.e. their connections) in each network. Network density reflects the share of existing edges with respect to all possible ones. We additionally report the fraction of mutual connections; that is, the fraction of cases when someone names someone else as a friend, these nominations are reciprocated. The average and global clustering coefficients measure the clustering tendency in the network as a whole, while the individual clustering coefficient introduced in Section 3.2.1, reflects how embedded a node is in her neighborhood. Furthermore, the tendency of individuals to be connected with nodes of similar connectivity is measured by the assortativity coefficient. Positive assortativity reflects that popular people are friends with popular people, while negative assortativity appears in networks in which connected individuals are connected to less connected ones. We also report two homophily indexes reflecting the interconnections or segregation of genders and people from different classrooms. Moreover, the average degree and in degree of the individuals in each network and their standard deviation are considered. The standard deviation of the degree reflects how hierarchical a network is. Last, we also check how the community structure (namely, the number of network communities or the number of large network communities) affects bullying.

Table 5: Summary statistics of the characteristics of each network (global measures of each different course and schools)

Variable	Obs	Mean	Std. Dev.	Min	Max
No. nodes (+)	3035	125.762	42.588	29	179
No. edges (+)	3035	1.480.796	616.788	212	2952
Density (+)	3035	.119	.087	.056	.454
Global reciprocity (+)	3035	.447	.089	.343	.726
Assortativity (+)	3035	-.006	.084	-.243	.184
Average in degree (+)	3035	11.789	2.528	7.277	17.93
Average degree (+)	3035	23.579	5.056	14.555	35.86
SD in degree (+)	3035	5.932	1.132	2.728	8.28
SD degree (+)	3035	14.717	3.448	5.499	23.188
Global clustering (+)	3035	.42	.1	.313	.732
Average clustering (+)	3035	.492	.091	.394	.781
SD clustering (+)	3035	.174	.033	.085	.229
G. Comp (+)	3035	124.071	41.242	28	178
No. isolates (+)	3035	1.576	2.892	0	12
Mean distance (+)	3035	2.448	.308	1.573	3.007
Diameter (+)	3035	5.906	1.237	3	9
Gender homophily (+)	3035	.306	.097	.079	.547
Group homophily (+)	3035	.449	.169	.09	1
Modularity (+)	3035	.337	.076	.136	.46
No. communities (+)	3035	6.425	3.593	3	18
No. important communities (+)	3035	4.913	1.246	2	7
No. nodes (-)	3035	125.762	42.588	29	179
No. edges (-)	3035	545.346	266.517	85	1159
Density (-)	3035	.044	.034	.014	.193
Global reciprocity (-)	3035	.118	.067	.035	.452
Assortativity (-)	3035	-.264	.097	-.517	.131
Average in degree (-)	3035	4.392	1.712	1.565	8.948
Average degree (-)	3035	8.784	3.424	3.13	17.897
SD in degree (-)	3035	3.553	1.036	1.845	6.023
SD degree (-)	3035	9.528	3.724	3.266	16.39
Global clustering (-)	3035	.147	.062	.06	.294
Average clustering (-)	3035	.271	.13	.07	.541
SD clustering (-)	3035	.226	.047	.148	.329
G. comp (-)	3035	120.339	41.06	29	178
No. isolates (-)	3035	5.138	5.692	0	23
Mean distance (-)	3035	3.529	.707	2.116	5.161
Diameter (-)	3035	8.737	2.302	4	15
Gender homophily (-)	3035	.017	.12	-.274	.249
Group homophily (-)	3035	.211	.219	-.388	1
Modularity (-)	3035	.315	.091	.164	.496
No. communities (-)	3035	10.853	6.542	3	30
No. important communities (-)	3035	5.676	1.51	2	8

3.3 Non-network variables

Additionally, we employ the following non-network measures as controls in Section 4:

I **School characteristics variables.** For each observation, we have information about the school to which they belong. We create a variable to differentiate the 11 schools, another to differentiate whether it is public, private, or semi-private, and another in which we identify the province in which it is located.

Table 6: Summary of school characteristics

Variable	Obs	Min	Max
School code	3,035	1	11
School type	3,035	0	2
School town	3,035	0	7
Grade	3,035	1	4
Group	3,035	1	7

II **Socio-demographic variables.** The first personal questions allow us to have *age* and gender[8] variables. There is also information on migrant-origin, *migrant* variable. We get information on the first and second generations, whether the students were born in Spain, but their parents migrated, or they have also migrated with them. We also have information about height and weight. However, we contemplate the possibility that some individuals prefer not to answer.

III **Behavior individual variables.** To measure academic performance, students register the number of A's and B's they achieved last year. The maximum that can be reported is 4. It asks about three core subjects (Language and literature, mathematics and English) and a free category of "other subjects". We create a discrete variable called *score*, from 0 to 8. The maximum score is only obtained if the student has achieved 4 A's, and the minimum means that you have not got any A's or B's. For example, if an individual has 3 A's, she gets a 7, or if she only has 4 B's, she will get a 4.

Self-esteem is measured with three questions regarding the school in general (*mood general*), their friends (*mood fun*) and loneliness[9] (*mood alone*). The same scale is used for all three, they have a discrete value from 0 to 4 depending on the frequency of the feeling. Considering the highest extreme value as a positive indicator and the values close to zero as a negative indicator.

[8] *Female* variable

[9] This variable is measured on an inverse scale with respect to the other variables.

Three questions from the cognitive reflection test are included and a normalized variable is created with the total, *crt*. In the same way, a normalized variable is created with the total of the three financial task questions, *fin*.

On the other hand, there are economic preference variables. We include a time-discount task to construct a variable that measures the patience of the individuals. There is also a risk-aversion task.

Table 7 presents the basic statistics of the variables that have been obtained through the survey. For each individual, we have information about the grade and group in which they are enrolled[10].

Table 7: Summary statistics of non-network variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Age	2,511	13.82	1.395	11	21
Female	2,436	2.443	13.702	0	99
Migrant	2,368	0.241	4.072	0	99
Mood: Alone	2,455	2.85	1.053	0	4
Mood: Fun	2,456	3.435	0.788	0	4
Mood: General	2,456	2.917	0.859	0	4
Fin	2,480	0.376	0.28	0	1
Crt	2,494	0.512	0.267	0	1
Risk	2,492	0.573	0.166	0	1
Patience	2,502	0.567	0.335	0	1

4 Results

In this section, we present our results. We first summarize the elicited networks and show that they resemble standard friendship and enmity networks in the literature. Then, we show to what extent the networks predict bullying victimization.

4.1 Positive vs. Negative Networks

For illustration, Figures 1 and 2 plot the same friendship networks in the four different grades in one school. In Figure 1, each node is colored according to her school year. The figure clearly shows that each network represents one school-year unit. In contrast, Figure 2 represents the same network, but the nodes are colored according to gender. We can see that, although many cross-gender friendships exist in the graphs, there is a visible tendency of gender homophily: girls are more likely to be friends with other girls, while boys tend to befriend boys.

[10] All data is anonymized and it is not possible to identify the participants.

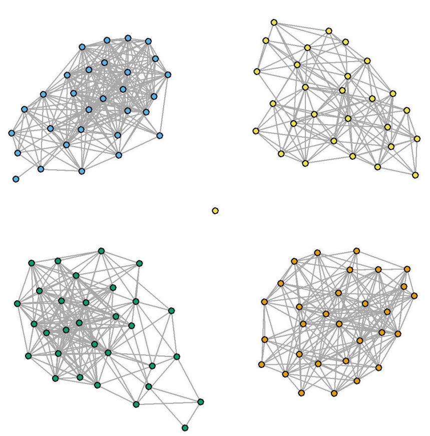

Figure 1: Friendship network colored by grade

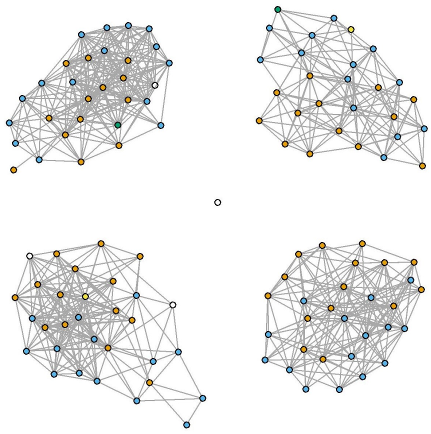

Figure 2: Friendship network colored by gender

Table 8 summarizes the global network characteristics disaggregated by the network type. Unlike Table 5 that considered the averages across the 30 networks, Table 8 compares the entire positive networks with the negative ones.

Firstly, the friendship and best-friendship networks exhibit the typical features of friendship networks observed in the literature Jackson (2011): the density of nodes is relatively compared to all possible links (0.3%), the reciprocation rate is around 50%, the number of isolated nodes is negligible, local clustering is considerably higher than in a comparable randomly generated network, popular people befriend popular ones as illustrated by the positive assortativity, the average distances are short, and there is typical homophily on gender (see also Figure 2) and class belonging. Although the average degree is high in the friendship network, it is comparable to other studies in the best-friendship one.

Although the number of nodes in each network is the same by construction, there is a large variability in the different network properties across the four network types. There are considerably more connections in the friendship than the corresponding enmity networks. As a result, large fraction of people are isolated in the enmity networks. Reciprocity and the clustering in the friendship networks exceed that of the enmity networks three- to fourfold. Interestingly, friendship networks exhibit positive assortativity, whereas enmity networks are disassortative. It means that people "hated" by many people tend to be hated by people that few people dislike.

Table 8: General characteristics of positive and negative networks: Global measurements

	Friends	Best Friends	Enemies	Worst enemies
Number of nodes	3,035	3,035	3,035	3,035
Number of edges	35,784	12,007	13,333	3,122
Density (possible edges)	0.00388	0.00130	0.00144	0.00034
Reciprocity	0.45025	0.38144	0.12360	0.09865
Degree: average	23.58089	7.91235	8.78616	2.05733
(Std. Dev.)	(15.88297)	(6.74629)	(10.75836)	(3.78667)
Giant component	179	176	180	151
Isolated nodes	30	166	121	1003
Clustering coefficient: total	0.41263	0.31937	0.17001	0.07154
Clustering coefficient: average	0.50461	0.45046	0.30659	0.15787
Degree correlation:	0.17172	0.08361	-0.06212	-0.11370
Diameter	3	6	4	9
Mean distance	2.10301	3.15178	2.40451	3.60126
Assortativity	0.09335	0.04157	-0.15590	-0.16327
Homophily (Gender)	0.29484	0.46091	0.03706	0.08926
Homophily (Class)	0.49239	0.51912	0.23593	0.32718

In contrast, we observe interesting similarities across the friendship and negative structures. Both networks contain giant components of similar sizes and both exhibit typical network hierarchies of social networks. The latter is corroborated by the comparison of the degree distribution in our networks with comparable random graphs in Figures 3 and 4.[11] The comparison of the degree distribution of the observed (red) and random (green) networks in Figures 3 and 4 clearly illustrate the typical "fat-tails" of socially generated social networks: too many people are either very peripheral (the left tail of the red degree distributions in Figures 3 and 4) or very connected (the right tail) as compared to the random networks. Hence, important social processes are behind forming friendship and enmity networks. The aim of this study is to test whether such hierarchy is connected with who is bullied in the schools and, therefore, whether the same processes behind the network formation may be driving bullying victimization.

[11]Comparable random networks are networks with the same number of nodes and connections in which the links are distributed randomly in the population.

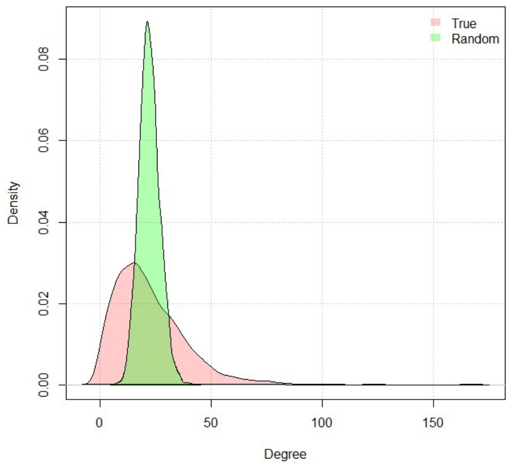

Figure 3: Comparison of the degree distribution of the friendship network. Red=True network; green=random network

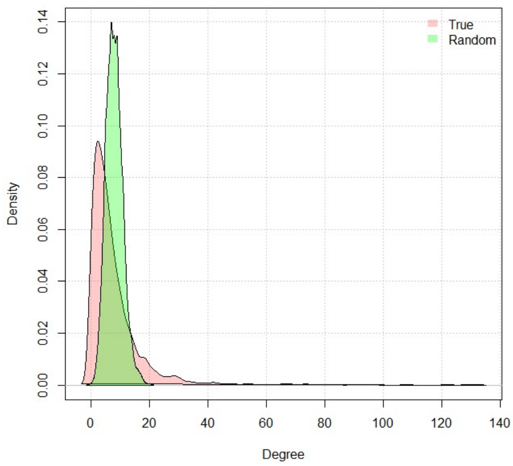

Figure 4: Comparison of the degree distribution of the enmity network. Red=True network; green=random network

4.2 Networks and Bullying

In this section, we analyze to what extent we can identify individuals who are being bullied using the information about the social networks summarized in the previous section.

We illustrate the idea using Figures 5 - 8 that plot the friendship, best-friendship, enmity, and worst-enmity networks, respectively. This time, we color the network members according to their victimization status. The majority of the nodes are white because most people do not suffer bullying. Blue nodes represent adolescents who self-report being bullied at school but are not named as victims by others. Yellow nodes correspond to students whom their classmates name as victims, but they do not self-report that.[12] Last, green nodes are cases of people who both self-report themselves and are reported by others as victims (corresponding to our variable intersection).

A close look at the four networks reveals a clear pattern: the victims tend to occupy peripheral positions in the friendship networks, while they find themselves in the center of the graphs in the enmity networks. In the case of negative and positive networks, these features are more evident when the links are stronger (i.e. in the best-friendship and worst-enmity networks).

[12]There are no such cases in Figures 5 - 8.

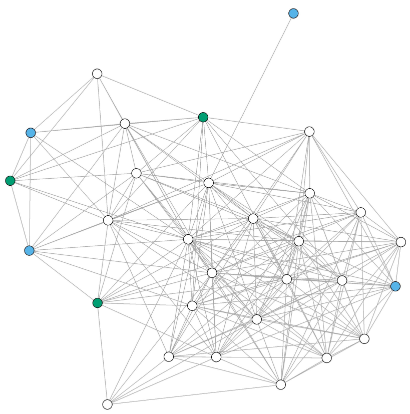

Figure 5: Friendship network in one school colored by bullying victimization. White = no bullying; blue = Self-reported; green = Intersection

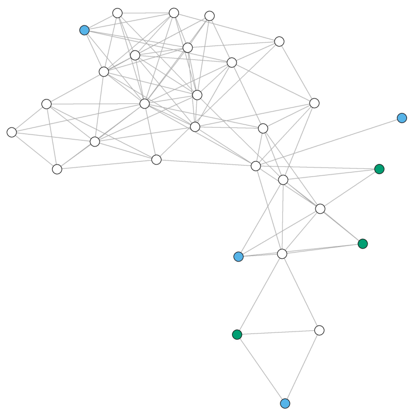

Figure 6: Best-friendship network in one school colored by bullying victimization. Colors defined as in Figure 5.

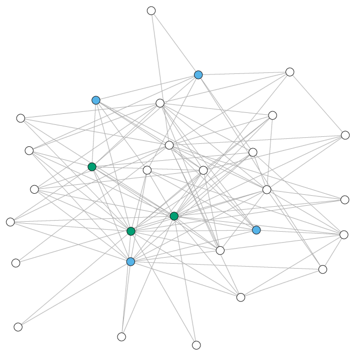

Figure 7: Enmity network in one school colored by bullying victimization. Colors defined as in Figure 5.

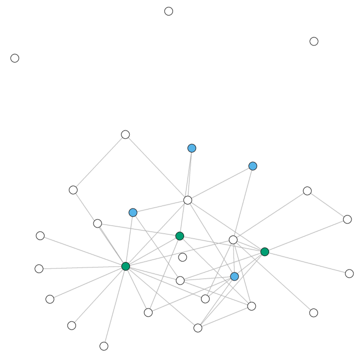

Figure 8: Worst-enmity network in one school colored by bullying victimization. Colors defined as in Figure 5.

In the following section, we formally test the observations using regression analysis. We mostly employ logistic regressions to predict whether a student is a victim of bullying, using the different network measures as predictors and other socioeconomic characteristics as control variables.

4.2.1 Bullying and individual positioning

In this section, we illustrate step by step the prediction ability of the positive networks only, followed by the negative networks only and finally, we incorporate both types into the statistical models. In the main part of the analysis, we focus on our bullying intersection as the dependent variable to save on space. The results for the other variables are qualitatively similar and we only report our results for the other dependent variables in Section 4.2.4, where we present our selected model.

As a starting point, we replicate the analysis presented by Mouttapa et al. (2004) who only use local variables and friendship networks. In this exercise, we obtain similar estimates but ours tend to be more significant, probably due to the greater statistical power of our sample size. We confirm that victims of bullying receive fewer friendship nominations and their friends are also more likely to be victims of bullying, but, as opposed to Mouttapa et al. (2004), our results are statistically strong. Using the enmity networks instead or combining both shows that the negative networks in a model Mouttapa et al. (2004) to Mouttapa et al. (2004) reveals that negative relationships deliver important and independent information from friendship networks while detecting the victims of bullying (see Appendix A.1 for details). Since our main models reported below extend the analysis of Mouttapa et al. (2004) considerably, we relegate the results of this replication analysis to Appendix A.1.

Table 9 reports the results of a more general model using the bullying intersection variable defined in Section 3, in which one is labeled as a victim if both she and others report her as such. We employ the logistic regressions and the different models differ as follows: model (1) only includes the friendship networks but, in contrast to Mouttapa et al. (2004), we introduce the density of students' network neighbourhoods (to analyze the effect of social cohesion) and global-centrality measures of each individual (to test whether the effect of centrality goes beyond one's immediate network neighborhood). Model (2) repeats this analysis replacing the friendship network with the enmity one; the remaining models combine both network types, but model (4) adds controls to the network variables and model (5) clusters the errors at the level of the network to account for possible correlations in the data. Table 9 also report McFadden's pseudo R^2 as measure of goodness of fit (McFadden, 1973); McFadden (1977) claims that a model has a good fit if the pseudo $R^2 > 0.2$ (see also Lee (2013)). Table 9 reveals that the friendship and enmity networks each separately explain 4-7% of the variability of the dependent variables. Since this number increases to over 10% in model (3), the information provided by each network type does not overlap much. If we include the traditional determinants considered in the literature, the predictability of our model rises to almost 30%.[13] The likelihood ratio chi-square tests illustrate that all our models clearly outperform a model without regressors. Furthermore, no model suffers from collinearity as the Variance Inflation Factor (VIF) is always

[13] All control variables are introduced in Section 3.3. Gender dummy never results significant, but, in line with the literature, the migrant dummy is a robust predictor of victimization.

well below 10.

As for the network variables, several centrality measures are significant predictors of bullying in the friendship network. In contrast, only the in-degree and the fraction of reciprocated enmities are significant in the model. In Section 4.2.4, we discuss the role of the individual variables in more detail.

Table 9: Results of regression of bullying and individual positioning. Logistic regression and individual-level analysis.

VARIABLES	(1) Intersection	(2) Intersection	(3) Intersection	(4) Intersection	(5) Intersection
Out degree (+)	0.042**		0.039**	0.035	0.035
In degree (+)	-0.141***		-0.141***	-0.208***	-0.208***
Betweenness (+)	0.000		0.000	0.002	0.002*
Eigenvector (+)	-3.870		-3.962	-4.712	-4.712**
Closeness (+)	-1.007		-0.765	-1.495	-1.495
Clustering (+)	0.768		0.588	0.860	0.860
Reciprocal degree (+)	-0.360		-0.273	0.744	0.744
Friend victims	2.549***		2.097***	0.848	0.848
Out degree (-)		0.013	0.008	0.006	0.006
In degree (-)		0.099***	0.079***	0.076**	0.076**
Betweenness (-)		0.000	0.000	-0.000	-0.000
Eigenvector (-)		0.167	0.408	-2.331	-2.331
Closeness (-)		-1.088	-1.259	-0.709	-0.709
Clustering (-)		-0.743	-0.663	-0.849	-0.849
Reciprocal degree (-)		-0.065	-0.028	0.675	0.675*
Enemy victims		0.485	0.301	-0.530	-0.530
Constant	-3.952***	-4.870***	-4.199***	-0.219	-0.219
Observations	3,035	3,035	3,035	2,241	2,241
Pseudo R^2	0.0750	0.0404	0.107	0.298	0.298
Prob< χ^2	0.0000	0.0000	0.0000	0.0000	
VIF	3.58	1.61	2.91	4.91	4.91
Controls	No	No	No	Yes	Yes
Cluster-Robust S.E.	No	No	No	No	Yes

*** p<0.01, ** p<0.05, * p<0.1
Friendship network (+), enmity network (-)
Probability of obtaining the χ^2 statistic, testing the overall model
Variance Inflation Factor, VIF<10 if no multicollinearity
Control variables described in Section 3.3
Robust standard errors clustered at network level (30 clusters)

Table 10 repeats the analysis from for models (4-5) in Table 9 for each gender separately. The analysis clearly reveals that who is bullied is clearly gender-specific. First of all, different network characteristics predict bullying victimization among men and women. Most importantly though, the ability to predict bullying (as illustrated by pseudo R^2) increases considerably with respect to the pooled regressions in Table 9. If predicted by gender separately, we can explain roughly 41% and 36% of the variability of the dependent variable in the case of men and women, respectively. Hence, predicting bullying victimization using networks should consider men and women separately.

Table 10: Results of regression of bullying and individual positioning by gender. Logistic regression and individual-level analysis.

	Males		Females	
	(1)	(2)	(3)	(4)
VARIABLES	Intersection	Intersection	Intersection	Intersection
Out degree (+)	-0.005	-0.005	0.088**	0.088**
In-degree (+)	-0.029	-0.029	-0.381***	-0.381***
Betweenness (+)	0.003*	0.003**	0.000	0.000
Eigenvector (+)	-3.203	-3.203	-158.432***	-158.432***
Closeness (+)	1.655	1.655	-1.894	-1.894
Clustering (+)	-1.316	-1.316	0.101	0.101
Reciprocal degree (+)	-3.012*	-3.012*	3.162***	3.162***
Friend victims	0.618	0.618	0.457	0.457
Out degree (-)	0.014	0.014	-0.002	-0.002
In degree (-)	0.070	0.070	0.110**	0.110**
Betweenness (-)	0.001	0.001	-0.000	-0.000
Eigenvector (-)	-948.680**	-948.680**	-0.309	-0.309
Closeness (-)	0.898	0.898	-10.701	-10.701
Clustering (-)	2.103*	2.103**	-1.374	-1.374
Reciprocal degree (-)	0.552	0.552	0.725	0.725
Enemy victims	-0.992	-0.992	-0.908	-0.908
Constant	5.877*	5.877*	-1.863	-1.863
Observations	840	840	1,072	1,072
Pseudo R^2	0.415	0.415	0.358	0.358
Prob< χ^2	0		0	
VIF	5.46	5.46	5.07	5.07
Controls	Yes	Yes	Yes	Yes
Cluster-Robust S.E.	No	Yes	No	Yes

*** p<0.01, ** p<0.05, * p<0.1
Friendship network (+), enmity network (-)
Probability of obtaining the χ^2 statistic, testing the overall model
Control variables described in Section 3.3
Clustered Standard Errors by network (30 clusters)

4.2.2 Bullying and network-wide characteristics

In this section, we verify whether global network measures can predict bullying victimization at the network level. Our dependent variable is the number of bullying victims in each network (that is, year-school unit) and the explanatory variables are network-wide characteristics. Hence, each regression is conducted with 30 observations. Since the global measures are highly correlated (see Appendix A.3 for correlation matrices), Table 11 presents numerous simple linear regressions, in which each model considers one unique global network characteristic but the same for both the friendship and enmity network (as well as controls). Therefore, models (1 - 9) in Table 11 only differ in the regressors listed in the first column of the table.

We estimate that the density of the enmity network is correlated with the instances of bullying in the network (model (1)), but this is not the case of friendship networks. Similarly, higher reciprocity of enmities and their higher homophily increases bullying (models (2) and (7)). Model (3) reveals a negative relationship between the average in-degree and bullying in the friendship network: more friendships decrease bullying. In contrast, in model (6), the relationship observed with the friendship network in the standard deviation of clustering is positive. The remaining global measures are never significant. All in all, certain network architectures might stimulate or mitigate bullying. We investigate this claim in the following section combining individual positioning and global network measures.

Table 11: Results of linear regression of bullying and network-wide characteristics

VARIABLES	(1) Intersection	(2) Intersection	(3) Intersection	(4) Intersection	(5) Intersection	(6) Intersection	(7) Intersection	(8) Intersection	(9) Intersection
Density (+)	-1.030								
Density (-)	13.057*								
Global reciprocity (+)		-3.199							
Global reciprocity (-)		8.802***							
Average in degree (+)			-0.136**						
Average in degree (-)			-0.033						
SD in degree (+)				-0.258					
SD in degree (-)				-0.221					
Global clustering (+)					-1.120				
Global clustering (-)					-1.675				
SD clustering (+)						12.600*			
SD clustering (-)						2.762			
Group homophily (+)							-0.009		
Group homophily (-)							1.500*		
Modularity (+)								-0.450	
Modularity (-)								-0.857	
No. communities (+)									0.021
No. communities (-)									-0.019
Constant	-0.706	0.022	2.477**	2.299**	1.868	-1.490	-0.088	0.933	0.730
Observations	30	30	30	30	30	30	30	30	30
R^2	0.360	0.471	0.359	0.354	0.285	0.366	0.418	0.282	0.284
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster-Robust S.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1
Friendship network (+), enmity network (-)
Control variables described in Section 3.3
Clustered Standard Errors by network (30 clusters)

4.2.3 Both individual positioning and global characteristics as predictors of bullying

In this section, we test whether individual positioning combined with global network measures can predict individual-level victimization. Table 12 presents nine logistic regressions. The benchmark model is a regression (5) from Table 9; we complement this model with the global network-wide measures one by one (as in Table 12 above).

We observe that in-degree is a robust predictor of victimization both in the friendship and enmity networks. In addition, global centrality measures, namely *eigenvector* or *betweenness*, in the friendship network also remain significant, suggesting the centrality protects from bullying beyond the effect of local in-degree. Victims tend to be less central in positive networks locally and globally. Centrality beyond the local neighborhood in enmity networks does not seem to contribute to bullying.

Regarding the global measures, the results mimic those in Table 11. Victims of bullying tend to belong to networks with fewer enmities where their reciprocity is higher. Low hierarchy (low standard deviation of degrees) in the enmity network prevents bullying. Moreover, a higher number of network subcommunities (reflected in both modularity and number of communities) stimulates victimization.

Overall, these results confirm that networks matter, but friendship and enmity networks on the one hand and different network features at the individual and global level, on the other, affect bullying differently.

Table 12: Results of regressions of bullying and individual positioning and global characteristics. Logistic regression and individual-level analysis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Intersection	Intersection	Intersection	Intersection	Intersection	Intersection	Intersection	Intersection	Intersection
Out degree (+)	0.028	0.031	0.040	0.033	0.027	0.037	0.040	0.029	0.034
In degree (+)	-0.206***	-0.193***	-0.178***	-0.189***	-0.203***	-0.206***	-0.166***	-0.209***	-0.215***
Betweenness (+)	0.002*	0.002*	0.001	0.002	0.002*	0.002	0.001	0.002**	0.002*
Eigenvector (+)	-5.083**	-5.265***	-3.356	-2.982	-4.336**	-4.998***	-4.719**	-6.846***	-4.401**
Clustering (+)	0.292	0.214	0.919	0.410	0.427	0.842	0.718	0.550	0.713
Closeness (+)	-3.971	-6.683	-1.514	-2.403	-2.141	-1.447	-4.225	-2.883*	-1.055
Reciprocal degree (+)	0.598	0.552	0.621	0.615	0.650	0.811	0.469	0.673	0.791
Friend victims	0.189	0.262	0.673	0.771	0.888	0.924	0.015	0.408	0.730
Out degree (-)	0.002	0.004	0.014	0.011	0.012	0.006	0.007	0.010	0.002
In degree (-)	0.071**	0.081**	0.121***	0.120***	0.097**	0.081**	0.099** 0.089**	0.078**	
Betweenness (-)	0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000
Eigenvector (-)	-1.786	-1.382	-1.981	-1.617	-1.322	-2.615	-0.088	-2.386	-2.220
Clustering (-)	-1.086	-0.881	-0.011	-0.146	0.098	-0.910	-0.238	-0.449	-0.782
Closeness (-)	-0.626	-0.752	-1.124	-1.143	-0.975	-0.814	-0.960	-0.889	-0.631
Reciprocal degree (-)	0.579	0.555	0.425	0.377	0.515	0.648	0.462	0.534	0.644
Enemy victims	-1.362	-1.467	-0.799	-0.875	-0.664	-0.494	-1.598*	-0.959	-0.445
Density (+)	0.434								
Density (-)	15.287								
Global reciprocity (+)		-0.201							
Global reciprocity (-)		7.883**							
Average in degree (+)			-0.141						
Average in degree (-)			-0.360***						
SD in degree (+)				-0.131					
SD in degree (-)				-0.722***					
Global clustering (+)					5.327**				
Global clustering (-)					-12.461*				
SD clustering (+)						1.764			
SD clustering (-)						3.438			
Group homophily (+)							1.920		
Group homophily (-)							2.356*		
Modularity (+)								-5.957*	
Modularity (-)								0.669	
No. communities (+)									-0.190**
No. communities (-)									0.040
Constant	-1.451	-1.691	2.632	2.813	-0.533	-1.134	-3.231	1.279	0.076
Observations	2,241	2,241	2,241	2,241	2,241	2,241	2,241	2,241	2,241
Pseudo R^2	0.313	0.322	0.318	0.325	0.314	0.299	0.329	0.311	0.307
VIF	5.62	6.90	6.59	7.39	7.26	8.26	5.61	6.31	5.24
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster-Robust S.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1
Friendship network (+), enmity network (-)
Control variables described in Section 3.3
Clustered Standard Errors by network (30 clusters)

4.2.4 Selecting final models

Since many variables in Table 12 are never significant, this section presents models in which we only restrict attention to dependent network variables that result significant in at least one regression. Since this leads to one unique model, Table 13 includes the selected model for each of the dependent variables introduced in Section 3: bullying intersection (model (1)), bullying union (2), self-reported bullying (3), other-reported bullying (4), and the number of times one is mentioned as a victim by others (5).

Being bullied is robustly related to the number of times one is named as a friend (popularity) positively and the number of times one is named as an enemy negatively. Moreover, global centrality in the friendship network consistently predicts bullying. Moreover, the higher the fraction of victims' enemies, the less likely she is a victim herself. At the network-wide level, segregation–measured by the number of communities and homophily on classroom–stimulates bullying.

The best fitting model is (1), where the dependent variable is the intersection; it explains 34%. Our models predict much less of the other dependent variables. However, if we select our models separately for each gender, the fit increases substantially. For example, Table 14 reports the intersection variable's case and shows that our model's predictive ability increases by 44.1% and 10.6% for males and females, respectively. Hence, once again, the gender-specific analysis is more suitable predicting victimization than the pooled analysis.

Table 13: Result of final logistic regression and individual-level analysis.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Intersection	Union	Self-R	Others-R	No. others-R
Out degree (+)	0.052*	0.008	0.021	0.009	0.003**
In degree (+)	-0.136***	-0.088***	-0.062**	-0.099***	-0.016***
Eigenvector (+)	-7.271***	-0.546	-5.630***	-0.095	0.062
In degree (-)	0.111***	0.125***	0.054**	0.140***	0.030***
Enemy victims	-1.686*	-0.416	-0.717	-0.456*	-0.090**
N. isolates (+)	-0.952***	0.096	-0.149	0.061	0.024
N. communities (+)	0.542*	-0.120*	0.053	-0.098	-0.024
Group homophily (-)	3.776***	1.200***	1.501***	1.407***	0.353***
Constant	-3.971**	0.637	-0.009	-0.234	0.653***
Observations	2,241	2,241	2,241	2,241	2,241
VIF	7.34	7.34	7.34	7.34	
(Pseudo) R^2	0.340	0.141	0.174	0.165	0.0972
Controls	Yes	Yes	Yes	Yes	Yes
Cluster-Robust S.E.	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1
Friendship network (+), enmity network (-)
Control variables described in Section 3.3
Clustered Standard Errors by network (30 clusters)

Table 14: Result of final logistic regression and individual-level analysis by gender.

	Males	Females
	(1)	(2)
VARIABLES	Intersection	Intersection
Out degree (+)		0.072**
In degree (+)		-0.317***
Eigenvector (+)	-5.169***	-151.192***
Betweenness (+)	0.003***	
Reciprocity (+)	-4.235***	2.567*
In degree (-)	0.148**	0.141**
Gender homophily (+)		-4.926***
Group homophily (+)		3.103***
N. important communities (+)		0.587***
Density (-)	60.246***	
Assortativity (-)	9.411**	
SD in degree (-)		-1.225***
Group homophily (-)	4.464***	
Constant	-9.209**	-0.744
Observations	858	1,077
Pseudo R^2	0.490	0.376
Controls	Yes	Yes
Cluster-Robust S.E.	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1
Friendship network (+), enmity network (-)
Control variables described in Section 3.3
Clustered Standard Errors by network (30 clusters)

5 Conclusions and Discussion

Since school bullying is by definition a social phenomenon, we ask to what extent friendship and enmity networks at school serve to identify the victims of bullying. Our results show that social organization as described by these networks provides a piece of quantitatively important and independent information about who suffers bullying in our data. We particularly observe that (i) both individual network positioning and network-wide organization play a role while predicting victimization, but different characteristics play a role at the individual vs. global level, and individual positioning seems to be somewhat more relevant than the global architecture; (ii) friendship and enmity networks play an orthogonal role in predicting victimization; and (iii) the way the network predict victimization differs considerably across both sexes.

Before we discuss the implications of our results for different theories of bullying in psychology and sociology, we would like to emphasize that our analysis is purely correlational. We do not claim that - nor does our data allow us to prove whether - specific network positioning leads to bullying or whether being a victim of bullying leads to specific network positions. In fact, we believe that both phenomena evolve hand in hand and none of them "causes" the other. We insist that our analysis is a simple fitting exercise which tests whether we use network data in order to predict who can suffer from bullying because observing who is bullied directly is for many reasons challenging.

How do our results relate to existing theories in the literature?

Bukowski and Sippola (2001) suggest the group dynamics theory that posits that victimized students are socially isolated because they do not contribute to the achievement and cohesion of the group and bullies target them. This approach simultaneously implies that victims should be isolated, but bullying results from a group social processes. (Nishina, 2004). We only partially confirm this theory: victims are entirely isolated but they have fewer friends and are less central in their networks. However, they do not exhibit lower cohesion in their neighborhoods. In addition, the only network-wide variable that robustly predicts victimization is the integration of people from different classrooms, suggesting that–rather than a within-group process–the origin of bullying stems from inter-group conflict.

Another explanatory perspective considers bullying as a result of power imbalances between students. Therefore, bullying may occur due to differences in personal power among adolescents and more powerful adolescents would oppress the less powerful ones (Rigby, 2004; Cillessen and Mayeux, 2004). Similarly, dominance theory explains how social networks influence bullying behaviors since aggressive behaviors generate social hierarchy (Hawley, 1999; Mouttapa et al., 2004). Lastly, the social rank theory provides similar arguments Hawker and Boulton (2001). We do not observe the bullies in our data, but we confirm these theories partially by showing that bullied individuals indeed occupy positions with lower social status in friendship networks (a result in line with other non-network studies testing these predictions; see e.g. Salmivalli and Isaacs (2005); Salmivalli (2010)).

Other people argue that friendship can serve as social collateral against bullying (Crick and Grotpeter, 1996). We confirm this by showing that people with more friends are less likely to be victimized. However, we contradict this theory by founding that reciprocal friendship (the relationships that one would consider stronger) does not robustly predict victimization.

Regarding the global organization of the groups, victims of bullying are more likely to find themselves in networks with more partially segregated communities (as described by the number of important communities and homophily in the classroom in our regressions). This rather suggests that conflict across subgroups rather than hierarchical establishment might be behind bullying. This claim should be formally tested though.

One of the main novelties of our study is to bring the enmity network into the analysis. Most theories refer to positive relationships and status, but most of them abstract from negative links in a group, although peer rejection also forms part of typical socialization processes (Sentse et al., 2015). Indeed, victims collect a larger number of enmity nominations and occupy central positions in the enmity networks. It is an open question to relate the positioning of victims in both the friendship vs. enmity networks.

Last, gender is a key variable in the bullying and aggression literature and we confirm the gender-specific nature of the phenomenon. Interesting patterns in the gender-specific regression deserve further investigation and relation to the existing theories of bullying.

Although our study provides an alternative picture of bullying, it does not come without limitations. Two main limitations (in fact, common in the literature) are the cross-sectional structure of our data and self-reported information on bullying. The first prevents us from making any causal claims from our analysis. The evolution of the relationships and bullying behavior over time would enable a dynamic analysis that might uncover whether network positioning drives bullying or vice versa. The problem of self-reports is alleviated by eliciting whether one mentions herself as well as other-reported bullying and by considering four different measures of bullying in our analysis. The fact that the different definitions of victimization deliver consistent results makes us confident that our results are generalizable, we cannot assess the degree of noise in our data.

These considerations notwithstanding, our results corroborate that bullying is a complex social behavior. Many factors at different social levels come into play and can vary considerably across age, gender, and location. We believe that our work will inform scientists, practitioners, and policymakers alike regarding the social processes behind the phenomenon of bullying.

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A Appendices

A.1 First appendix

We replicated the Mouttapa et al. (2004) analysis. In this analysis, we only focus on friendship networks. Four logistic regression models are estimated to explain the binary variables of bullying and just one linear regression in the last place. Table 15 contains the coefficients.

Table 15: Results of logistic regression of victims variables: positive network

VARIABLES	(1) Intersection	(2) Union	(3) Self-R	(4) Others-R	(5) No. others-R
Out degree	0.035**	0.008	0.008	0.012	0.003*
	(0.017)	(0.009)	(0.015)	(0.009)	(0.002)
In degree	-0.185***	-0.088***	-0.085***	-0.101***	-0.016***
	(0.045)	(0.017)	(0.028)	(0.018)	(0.003)
Reciprocal degree	1.167	0.224	0.347	0.316	0.039
	(0.769)	(0.314)	(0.509)	(0.343)	(0.062)
Friend victims	1.413*	2.792***	1.643***	2.770***	0.685***
	(0.741)	(0.422)	(0.611)	(0.437)	(0.140)
Migrant	0.038**	0.024***	0.026**	0.026***	0.004
	(0.015)	(0.009)	(0.013)	(0.009)	(0.002)
Constant	-3.601***	-1.563***	-2.982***	-1.719***	0.247***
	(0.473)	(0.202)	(0.340)	(0.217)	(0.040)
Observations	2,368	2,368	2,363	2,368	2,368
(Pseudo) R^2	0.0836	0.0644	0.0356	0.0701	0.046
Prob >F (χ^2)	0.0000	0.0000	0.0001	0.0000	0.0000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Hence, it is confirmed that victims of bullying receive fewer nominations, regardless of whether they have self-reported or have been reported by other peers. Furthermore, the count of friends who are bullied is also significant. Victims have more friends who are also victims of bullying.

Moreover, considering model (1)[14], which reflects the intersection, the measure *out degree* is also significant.

This same model is estimated by gender, presenting the results in Table 16. *In degree* is significant in all four models, while the attributes of friends are only significant in the union. However, it is noteworthy that there are differences regarding gender. Model (3) indicates that women included in the intersection cases, who suffer bullying, tend to mention more friends and noticeably have more reciprocal friends.

[14]It is verified that the model does not present multicollinearity problems, it has an average VIF of 3.18

Table 16: Results of logistic regression of victims variables by gender

	Males		Females	
	(1)	(2)	(3)	(4)
VARIABLES	Intersection	Union	Intersection	Union
Out degree	0.020	0.004	0.064**	0.011
	(0.022)	(0.012)	(0.027)	(0.014)
In degree	-0.107*	-0.099***	-0.289***	-0.085***
	(0.060)	(0.020)	(0.074)	(0.030)
Reciprocity	-0.807	0.182	2.688***	0.480
	(1.515)	(0.418)	(0.941)	(0.507)
Friend victims	2.020	2.949***	0.797	2.521***
	(1.501)	(0.639)	(0.936)	(0.589)
Migrant	-0.010	0.020*	0.052***	0.028**
	(0.017)	(0.011)	(0.018)	(0.014)
Constant	-3.465***	-1.117***	-3.668***	-2.052***
	(0.730)	(0.298)	(0.634)	(0.296)
Observations	1,137	1,137	1,089	1,089
Pseudo R^2	0.0552	0.0808	0.145	0.0545
Prob< χ^2	0.0110	0.0000	0.0003	0.0000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Similarly, an analysis of negative networks is performed. In this case, instead of including the count of friends who are bullied, we take into account the enemies who are bullied.

Table 17: Results of logistic regression of victims variables: negative network

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Intersection	Union	Self-R	Others-R	No. others-R
Out degree	0.017**	0.005	0.019***	-0.002	0.002
	(0.008)	(0.007)	(0.006)	(0.009)	(0.002)
In degree	0.092***	0.111***	0.063***	0.120***	0.026***
	(0.019)	(0.013)	(0.017)	(0.013)	(0.005)
Reciprocity	0.555	-0.089	-0.230	0.036	0.047*
	(0.398)	(0.177)	(0.277)	(0.193)	(0.029)
Victim enemies	0.315	0.289	0.043	0.350	0.049
	(0.560)	(0.242)	(0.396)	(0.259)	(0.041)
Migrant	0.032***	0.022**	0.025**	0.024**	0.003
	(0.010)	(0.010)	(0.011)	(0.010)	(0.002)
Constant	-5.178***	-2.697***	-3.868***	-2.945***	0.007
	(0.334)	(0.137)	(0.213)	(0.151)	(0.026)
Observations	2,368	2,368	2,368	2,368	2,368
(Pseudo) R^2	0.0477	0.0487	0.0272	0.0567	0.035
Prob > F (χ^2)	0.0000	0.0000	0.0000	0.0000	0.0000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results obtained with the negative network are similar to those with the positive network. Mentions received as enemies are significant in all models. However, except for in degree, no other variable is significant in all models. In models (1) and (3), mentions made stand out. The more enemies mentioned, the more likely it is to be bullied and self-report it.

Table 18 shows the model by gender. In the case of men, the mentions received as enemies are significant as in the previous model. On the contrary, in the female model (3), the degree of reciprocity also stands out, the victims tend to have more bad reciprocal relationships.

Table 18: Results of regression: negative network by gender

	Males		Females	
	(1)	(2)	(3)	(4)
VARIABLES	Intersection	Union	Intersection	Union
Out degree	0.017	-0.002	0.016*	0.016*
	(0.012)	(0.010)	(0.009)	(0.008)
In degree	0.120***	0.150***	0.075***	0.095***
	(0.034)	(0.019)	(0.026)	(0.018)
Reciprocity	-0.178	-0.261	0.957**	-0.045
	(0.799)	(0.233)	(0.440)	(0.288)
Victim enemies	0.478	-0.014	0.201	0.855**
	(0.904)	(0.312)	(0.748)	(0.407)
Migrant	-0.006	0.021	0.040***	0.023*
	(0.015)	(0.014)	(0.012)	(0.014)
Constant	-5.254***	-2.441***	-5.031***	-3.152***
	(0.537)	(0.184)	(0.423)	(0.222)
Observations	1,137	1,137	1,089	1,089
Pseudo R^2	0.0477	0.0680	0.0628	0.0557
Prob > χ^2	0.0002	0.0000	0.0410	0.0000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Results of regression: positive network (Best friends)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	bullying_intersection	bullying_union	self_bullying	others_bullying	n_others_bullying
Out degree	0.016	0.023**	-0.003	0.030***	0.008***
	(0.013)	(0.009)	(0.021)	(0.010)	(0.003)
In degree	-0.269***	-0.198***	-0.172***	-0.209***	-0.031***
	(0.099)	(0.033)	(0.066)	(0.036)	(0.005)
Reciprocity	0.063	0.275	-0.499	0.484**	0.108***
	(0.523)	(0.202)	(0.395)	(0.213)	(0.039)
Best friend victims	1.440***	2.369***	1.551***	2.328***	0.519***
	(0.536)	(0.297)	(0.439)	(0.299)	(0.106)
Migrant	-0.005	0.028***	-0.151	0.030***	0.004*
	(0.012)	(0.010)	(0.486)	(0.010)	(0.002)
Constant	-3.624***	-1.819***	-2.822***	-2.079***	0.166***
	(0.364)	(0.153)	(0.284)	(0.162)	(0.027)
Observations	2,368	2,368	2,363	2,368	2,368
R^2					0.041
Pseudo R^2	0.0470	0.0717	0.0428	0.0734	
Prob > χ^2	0.0005	0.0000	0.0000	0.0000	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 20: Positive and Negative Network Regression Results: Out degree

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Intersection	Intersection	Intersection	Intersection	Intersection	Intersection	Intersection	Intersection
Out degree (+)	0.012	0.003	0.007	0.019	0.019	0.018	0.019	0.001
Out degreee (-)	0.018***	0.020***	0.021***	0.012	0.011	0.010	0.010	0.012
Reciprocity (+)		-1.203**	-1.161**	-1.137*	-1.167**	-1.220**	-1.125*	-0.714
Reciprocity (-)		0.285	0.313	0.330	0.233	0.246	0.416	1.223***
Eigenvector (+)			-5.561	-6.021	-6.065	-5.980	-5.613	-6.465
Eigenvector (-)			0.521	0.586	0.557	0.610	0.258	-2.507
Betweenness (+)				-0.001	-0.001	-0.001	-0.001	0.001
Betweenness (-)				0.000***	0.000***	0.000***	0.000***	0.000
Closeness (+)					-1.053	-1.067	-0.924	-2.077
Closeness (-)					-1.205	-1.184	-1.007	-0.167
Clustering (+)						0.275	0.210	0.306
Clustering (-)						-0.208	-0.324	-0.763
Friend victims							2.715***	1.223
Enemy victims							0.399	-0.120
Constant	-4.675***	-4.054***	-4.102***	-4.182***	-4.055***	-4.121***	-4.553***	-0.116
Observations	3,035	3,035	3,035	3,035	3,035	3,035	3,035	2,241
Pseudo R^2	0.00877	0.0185	0.0263	0.0338	0.0362	0.0366	0.0557	0.235
Prob< χ^2	0.0010	0.0003	0.0004	0.0011	0.0042	0.0025	0.0000	0.0000
Controls	No	No	No	No	No	No	No	Yes

*** p<0.01, ** p<0.05, * p<0.1
Friendship network (+), enmity network (-)
Control variables described in Section 3.3

Table 21: Positive and Negative Network Regression Results: In degree

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Intersection	Intersection	Intersection	Intersection	Intersection	Intersection	Intersection	Intersection
In degree (+)	-0.102***	-0.104***	-0.096***	-0.115***	-0.117***	-0.123***	-0.120***	-0.195***
In degree (-)	0.102***	0.101***	0.102***	0.094***	0.094***	0.094***	0.084***	0.072**
Reciprocity (+)		-0.781	-0.837	-0.658	-0.681	-0.752	-0.758	0.337
Reciprocity (-)		-0.264	-0.246	-0.198	-0.309	-0.266	-0.094	0.648
Eigenvector (+)			-4.607	-4.140	-4.287	-3.917	-3.521	-3.754
Eigenvector (-)			0.546	0.781	0.683	0.883	0.763	-2.320
Betweenness (+)				0.001	0.001	0.001	0.001	0.003***
Betweenness (-)				0.000	0.000	0.000	0.000	0.000
Closeness (+)					-1.226**	-1.164*	-1.109*	-1.783
Closeness (-)					-1.473	-1.429	-1.295	-0.715
Clustering (+)						0.580	0.477	0.789
Clustering (-)						-0.791	-0.814	-0.974
Friend victims							2.054***	0.815
Enemy victims							0.316	-0.525
Constant	-3.975***	-3.401***	-3.427***	-3.519***	-3.369***	-3.399***	-3.660***	0.363
Observations	3,035	3,035	3,035	3,035	3,035	3,035	3,035	2,241
Pseudo R^2	0.0607	0.0701	0.0732	0.0783	0.0821	0.0855	0.0977	0.294
Prob< χ^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Controls	No	No	No	No	No	No	No	Yes

*** p<0.01, ** p<0.05, * p<0.1
Friendship network (+), enmity network (-)
Control variables described in Section 3.3

Table 22: correlation coefficients local measures

Variables	(1)	(2)	(3)	(4)
(1) Out degree (+)	1.000			
(2) Out degree (-)	0.095	1.000		
	(0.000)			
(3) In degree (+)	0.410	0.045	1.000	
	(0.000)	(0.013)		
(4) In degree (-)	-0.009	0.107	-0.013	1.000
	(0.635)	(0.000)	(0.487)	

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Table 23: Correlation coefficients global measures (positive network)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(1) Num nodes (+)	1.000																				
(2) Num edges (+)	0.847	1.000																			
	(0.000)																				
(3) Density (+)	-0.826	-0.547	1.000																		
	(0.000)	(0.000)																			
(4) Global reciprocity (+)	-0.751	-0.560	0.774	1.000																	
	(0.000)	(0.000)	(0.000)																		
(5) Assortativity (+)	0.237	0.011	-0.389	-0.151	1.000																
	(0.000)	(0.528)	(0.000)	(0.000)																	
(6) Average in degree (+)	-0.017	0.475	0.383	0.184	-0.391	1.000															
	(0.337)	(0.000)	(0.000)	(0.000)	(0.000)																
(7) Average degree (+)	-0.017	0.475	0.383	0.184	-0.391	1.000	1.000														
	(0.337)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)															
(8) SD degree (+)	0.698	0.913	-0.372	-0.434	-0.053	0.589	0.589	1.000													
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)														
(9) SD in degree (+)	0.588	0.793	-0.258	-0.268	-0.075	0.588	0.588	0.867	1.000												
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)													
(10) Global clustering (+)	-0.874	-0.655	0.941	0.848	-0.219	0.270	0.270	-0.475	-0.323	1.000											
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)												
(11) Average clustering (+)	-0.853	-0.603	0.930	0.805	-0.369	0.313	0.313	-0.403	-0.346	0.958	1.000										
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)											
(12) SD clustering (+)	0.399	-0.035	-0.572	-0.266	0.525	-0.744	-0.744	-0.074	-0.120	-0.446	-0.468	1.000									
	(0.000)	(0.053)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)										
(13) G. component (+)	0.997	0.860	-0.829	-0.763	0.222	0.003	0.003	0.709	0.585	-0.880	-0.847	0.372	1.000								
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.851)	(0.851)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)									
(14) No. isolates (+)	0.456	0.194	-0.319	-0.178	0.278	-0.272	-0.272	0.153	0.286	-0.291	-0.430	0.512	0.391	1.000							
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)								
(15) Mean distance (+)	0.637	0.249	-0.858	-0.618	0.406	-0.599	-0.599	0.048	0.082	-0.749	-0.804	0.647	0.629	0.360	1.000						
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)							
(16) Diameter (+)	0.503	0.173	-0.721	-0.562	0.270	-0.537	-0.537	0.030	0.049	-0.660	-0.726	0.493	0.497	0.285	0.864	1.000					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.100)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
(17) Gender homophily (+)	0.309	0.041	-0.516	-0.354	0.308	-0.445	-0.445	0.033	0.026	-0.457	-0.445	0.534	0.306	0.195	0.428	0.326	1.000				
	(0.000)	(0.023)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.066)	(0.152)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
(18) Group homophily (+)	-0.382	-0.361	0.210	0.495	0.157	-0.211	-0.211	-0.468	-0.516	0.290	0.261	0.042	-0.386	-0.115	-0.184	-0.222	-0.279	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.021)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
(19) Modularity (+)	0.361	0.004	-0.699	-0.306	0.333	-0.568	-0.568	-0.204	-0.227	-0.492	-0.510	0.560	0.358	0.185	0.759	0.578	0.387	0.179	1.000		
	(0.000)	(0.820)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
(20) No. communities (+)	0.642	0.373	-0.476	-0.344	0.328	-0.257	-0.257	0.318	0.398	-0.467	-0.581	0.566	0.587	0.958	0.466	0.377	0.259	-0.230	0.212	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
(21) No. important comm. (+)	0.833	0.670	-0.686	-0.721	0.266	-0.085	-0.085	0.586	0.453	-0.778	-0.735	0.369	0.841	0.267	0.497	0.434	0.299	-0.495	0.150	0.505	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Table 24: Correlation coefficients global measures (negative network)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(1) No. nodes (-)	1.000																				
(2) No. edges (-)	0.610	1.000																			
	(0.000)																				
(3) Density (-)	-0.778	-0.183	1.000																		
	(0.000)	(0.000)																			
(4) Global reciprocity (-)	-0.541	-0.207	0.783	1.000																	
	(0.000)	(0.000)	(0.000)																		
(5) Assortativity (-)	-0.003	-0.259	-0.172	-0.153	1.000																
	(0.863)	(0.000)	(0.000)	(0.000)																	
(6) Average in degree (-)	-0.096	0.700	0.490	0.216	-0.284	1.000															
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)																
(7) Average degree (-)	-0.096	0.700	0.490	0.216	-0.284	1.000	1.000														
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)															
(8) SD degree (-)	0.234	0.837	0.095	-0.158	-0.409	0.830	0.830	1.000													
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)														
(9) SD in degree (-)	0.026	0.714	0.384	0.187	-0.242	0.903	0.903	0.732	1.000												
	(0.155)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)													
(10) Global clustering (-)	-0.622	0.113	0.791	0.533	-0.079	0.699	0.699	0.349	0.670	1.000											
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)												
(11) Average clustering (-)	-0.121	0.537	0.367	0.054	-0.463	0.772	0.772	0.858	0.662	0.588	1.000										
	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)											
(12) SD clustering (-)	0.326	0.263	-0.309	-0.315	-0.259	-0.022	-0.022	0.426	-0.032	-0.147	0.506	1.000									
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.235)	(0.235)	(0.000)	(0.082)	(0.000)	(0.000)										
(13) G. component (-)	0.990	0.687	-0.728	-0.509	-0.043	0.005	0.005	0.337	0.105	-0.563	-0.016	0.364	1.000								
	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)	(0.789)	(0.789)	(0.000)	(0.000)	(0.000)	(0.370)	(0.000)									
(14) No. isolates (-)	0.316	-0.358	-0.528	-0.364	0.253	-0.692	-0.692	-0.620	-0.531	-0.549	-0.724	-0.156	0.177	1.000							
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)								
(15) Mean distance (-)	0.578	-0.007	-0.615	-0.473	0.257	-0.461	-0.461	-0.352	-0.303	-0.563	-0.545	-0.157	0.501	0.640	1.000						
	(0.000)	(0.700)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)							
(16) Diameter (-)	0.476	-0.052	-0.531	-0.440	0.355	-0.433	-0.433	-0.383	-0.273	-0.517	-0.570	-0.303	0.399	0.605	0.917	1.000					
	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
(17) Gender homophily (-)	0.461	0.243	-0.413	-0.351	-0.046	-0.134	-0.134	0.122	-0.001	-0.293	0.064	0.440	0.434	0.281	0.357	0.302	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.000)	(0.000)	(0.000)	(0.963)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
(18) Group homophily (-)	-0.105	-0.324	0.280	0.478	0.264	-0.238	-0.238	-0.485	-0.156	0.036	-0.354	-0.350	-0.136	0.168	0.125	0.225	-0.088	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.049)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
(19) Modularity (-)	0.446	-0.301	-0.673	-0.342	0.342	-0.708	-0.708	-0.648	-0.544	-0.649	-0.749	-0.172	0.339	0.803	0.675	0.652	0.228	0.265	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
(20) No. communities (-)	0.442	-0.278	-0.623	-0.405	0.254	-0.710	-0.710	-0.583	-0.522	-0.635	-0.712	-0.075	0.310	0.976	0.701	0.663	0.376	0.150	0.826	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
(21) No. important comm (-)	0.599	0.004	-0.765	-0.597	0.091	-0.533	-0.533	-0.210	-0.454	-0.774	-0.375	0.207	0.552	0.447	0.550	0.574	0.473	-0.078	0.589	0.572	1.000
	(0.000)	(0.826)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	