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Student Network Centrality and Academic Performance: Evidence from United Nations University

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Student Network Centrality and Academic Performance

-----Evidence from United Nations University[1]

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Abstract

In this paper we empirically studied the relationship between network centrality and academic performance among a group of 47 PhD students from UNU-MERIT institute. We conducted an independent email survey and relied on social networks theory as well as standard econometric procedures to analyse the data. We found a significant reversed U-shaped relation between network centrality and students' academic performance. We controlled our results by several node's characteristics such as age, academic background, and research area. Additional evidence shows that there is a negative impact of age on academic performance at PhD student level. Contributions of this paper can refer to the input into studies that aim to explore peer-effect. Also it contributes to the methodological approach by combining elements of network analysis and econometric theories. This study demonstrates that when evaluating the impact of network centrality on performance, there is no significant difference between various network centrality measurements.

JEL : D85, I21, I23, L14

Keywords : Networks analysis, Network centrality, Peer-effect, Academic performance

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1. INTRODUCTION

Social network analysis in recent decades has increasingly attracted researchers' attention. The rising interest in this topic is attributed to the notation of "interdependent social actors" and "the 'flow' of resource along the relational linkages between actors" (Wellman, 1988a). Amongst many methodologies in network analysis, graph theory is widely applied. It is a theory by considering nodes as actors and lines as ties. Three fundamental terms are embedded in graph theory, which are nodal degree, graph density, and network component.

Since 1950s when network analysis was initially introduced by Bavelas (1950), network centrality and its role in different environments have been widely studied. Researchers used a number of centrality measurements from different sides (such as relative and absolute, or local and global centralities). Of there, Nieminen (1974) defines a node is *locally* central if it has a large number of connections with the other points in its immediate environment. Freeman (1979, 1980a) argued that a node is *globally central* when it has a position of strategic significance in the overall structure of the network. In spite that many schools of network centrality studies have been blooming in the past decades and they compete each other, scholars make consensus that three main measurements on network centrality are most widely accepted: (1) degree-based network centrality that evaluates local centrality and uses comparison of the various nodal degree; (2) closesness-oriented centrality that is the global centrality and considers geodesic path between different nodes; and (3) Betweeness-oriented centrality that is local centrality and shows the extent to which a particular point lies "between" the various other points in the graph.

In the empirical vein, scholars applied experiments on network analysis. For example, Sacerdote(2001) measured the characteristics of peer effects by using network data; Manski (1993) evluated causal effect of peers' choice by choosing data from campus; Sacerdote (2001) argued that peer effects need to be paid attention especially when evaluating students' grade point average (GPA); and Hoxby and Weingarth (2005) demonstrated that the effect of peers' achievement is more important to measure monotonicity property than any other peer's attributes. Even though a large number of studies made contribution at empirical level, network data evidence on the relation between the intensity of connections with peers and academic performance has not yet been provided. Because of a limited number of studies in this field, especially in the context of international PhD students among whom interaction may tend to be relatively scarce in a very high variety of cultures and backgrounds, we in this paper aim to identify the relationship between different levels of peers interaction and its impact on academic performance, by using questionnaire to get data from 47 PhD students in the "Economics and Policy Studies of Technical Change" at UNU-MERIT. Our research question is *"To what extent does PhD students' network centrality at the individual level have executed impact over students' academic performance?"*

This paper is structured as follows. Section 2 and 3 presented data and methods respectively with theoretical model and research hypotheses. Section 4 offered network analysis results and econometric estimation. Section 5 provided conclusion and academic contributions.

2. DATA

The data was collected in Dec. 2008 from a series of independent email surveys distributed within a group of 48 United Nations University PhD students who were pursuing PhD studies at UNU-MERIT during the fall semester of 2008. The survey was conducted based on the questionnaire designed in the form of matrix. The questionnaire not only asked the questions about academic and social life, but also collected information associated with individual and academic characteristics of the respondents[2]. The list of the students was obtained from the website of the PhD Program in Economics and Policy Studies of Technical Change[3]. One observation was deleted since he/she did not reply the survey and with him/her no one declared to have communication. Our sample was eventually composite of 47 observations. We claimed that all information involving personal privacy was kept confidential, thereafter in this study each student was labeled as number randomly.

The response rate of the questionnaire was 73% (35 over 47 students). The missing data was filled up by assigning the number of ties to those who were actually out of the responding list

[2] A copy of the questionnaire is included in the appendix.
[3] The list of students was obtained from http://www.merit.unu.edu/phd/phdI/students.php in November of 2008

but were claimed by others having interactions[4]; the number of ties was computerized by summing up the direct ties between missing values and existing values. We used two strategies to collect node information of each missing item. In some cases for example the missing data is related to respondent's age, PhD work progress, and paper publications, we collected information from the UNU-MERIT secretary. In the other cases that missing data is related to subjective variables such as participation in seminars and weekly hours of work, missing data was imputed by assuming as the average value of all respondents. Our robust tests indicated that the overall results were not biased even in the case that we do not standardize the missing data.

3. METHOD

3.1 Dependent Variable

The purpose of this study is to empirically assess the relationship between students' social networks and academic performance. In order to overall estimate student's working performance, we design an indicator PhD progress index (PPI) as dependent variable. By using this indicator, the working performance of students from different batches could be standardized and measured. Specific to UNU-MERIT PhD educating system which includes one year PhD training and three years academic PhD research, the student's working performance needs to be valued from three perspectives: (1) the number of published articles; (2) PhD progress as well as working papers published in UNU-MERIT; (3) and frequency of seminar participation. The main idea of this index comes from the human development index (HDI) published every year by UNDP (United Nations Development Program). The main characteristic of this performance index (PI) is that it considered the progress of the PhD program as a main factor. In this case, all the other variables only affect performance positively in a smaller scale. In other words, if the value of the other variables were 0, the Performance Index would be equal to the value of progress index.

According to the importance of each perspective, we gave the respective weight on PhD progress index (PPI), saying that progress on time will be 1, progress in advance will be 1.5, and

[4] It is because a programmed data imputation process is widely applied in network analysis to fill in missing values with symmetric counterparts and is proven to be particularly useful in a context of a high response rate.

progress delayed will be 0.5. We set published or submitted paper index (PSPI) as Individual number of PSP divided by Total number of PSP; working papers at UNU-MERIT Index (WPUI) as Individual number of WPU divided by Total number of WPU; and Frequency of seminar participation index (FSPI) as Individual FSP divided by Total FSP. Therefore, the dependent variable which is made as integrative working Performance_Index is eventually equal to

$$Performance\_Index = PPI * (1 + PSPI) * (1 + WPUI) * (1 + FSPI)$$

3.2 Independent Variables

As required, the independent variables were set as network centrality. According to our primary experiments on network components, it can be sure that the networks centrality involved in this study was local-oriented. Therefore, we used index such as nodal degree and betweeness to measure network centrality X_1. Moreover, in order to identify the marginal effect of centrality on performance, we additionally set another independent variable Squared Centrality X_2.

3.3 Control Variables

Control variables were set according to the principle that PhD students' working performance is moreover affected by some other students' attributes. We therefore had control variables such as working attitude, age, research field, and previous academic background etc. Specifically indicating that at UNU-MERIT PhD students were selected from different countries' universities worldwide and the academic background is diversified (Economics, Management, Engineering, and Anthropology or other social sciences). Since PhD research at UNU-MERIT is classified into five groups, in the estimation in the next section, the dummy variables were given as follows: 1-"Micro-based evidence research on innovation and technological change", 2-"The role of technology in growth and development", 3-"Knowledge and industrial dynamics", 4-"Innovation, global business strategies and host country development" and 5-"The governance of science technology and innovation". All in all, we had six control variables as below.

$X_3 =$ Average working hours per week

$X_4 =$ Age

$X_5 =$ Academic Background Dummies

$X_6 =$ Areas of Research Dummies

$X_7 =$ Frequency of communication with supervisors (times per month)

$X_8 =$ Percentage of PhD research period spent in Maastricht

Table 1 shows statistics description of the variables. 47 observations are included. Academic performance index ranges from 0.5 to 1.7 with a mean of 0.8. Weekly hours of work ranges from 4 to 60 with an average of 39. The youngest PhD student in our sample is 26 years old while the oldest is 49 and the average is 31. The descriptive statistics of nodal degree and betweeness in social life and academic networks are listed as well.

Table1 Descriptive statistics

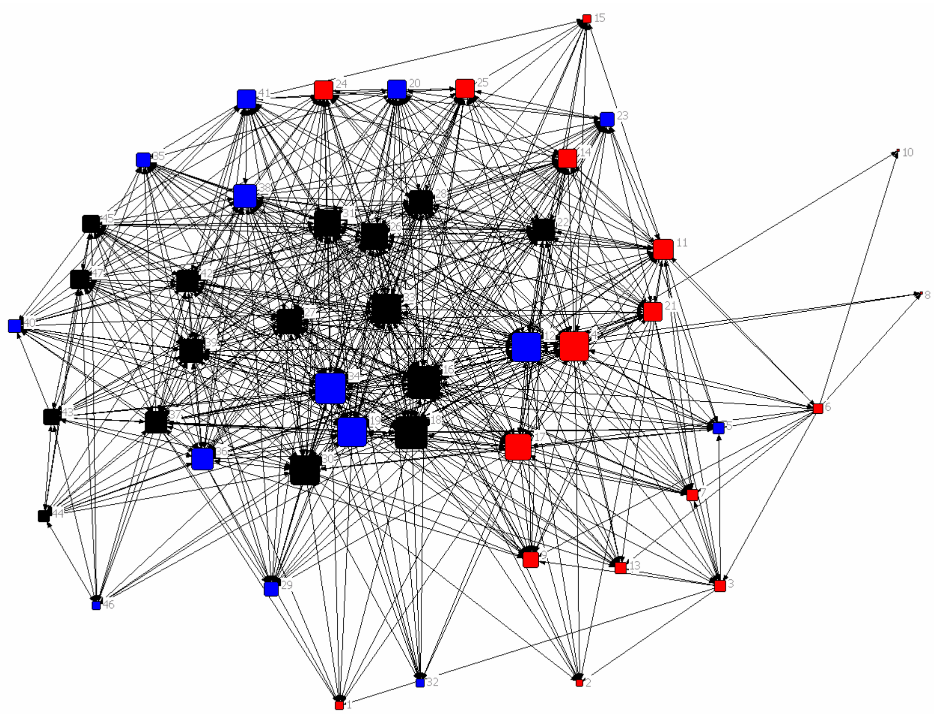
Variable	Observations	Mean	Std. Dev.	Min	Max
Academic Performance Index	47	0.8216716	0.3511721	0.5	1.791537
Degree (Social life Network)	47	54.82979	31.31906	6	124
Degree squared (S.L. Network)	47	3966.319	4066.898	36	15376
Betweeness (Social life Network)	47	14.95747	22.28941	0	97.633
Betweeness squared (S. L.Network)	47	709.9731	1856.717	0	9532.203
Degree (Academic Network)	47	27.48936	18.91614	3	87
Degree squared (A. Network)	47	1105.872	1400.384	9	7569
Betweeness (Academic Network)	47	30.55317	44.45374	0	180.932
Betweeness squared (A. Network)	47	2867.586	6696.157	0	32736.39
Topic 1	47	.0212766	.145865	0	1
Weekly hours of work	47	38.93617	10.30282	4	60
Age	47	31.48936	7.125802	26	49

3.4 Method

According to the information contained in our database, we firstly used UNCINET 6 to draw 4 networks: *social life network, academic network, life help network, and academic help network*. Networks were analyzed based on centrality (nodal degree, betweenness) and nodes' attributes included students' academic performance, batch, age, and self reported working hours etc.

We made a series of experiments on network drawing, ranging from weakest interactions (frequency lower than 2 in a scale from 0 to 4) to the strongest connections (higher than 3). We looked at network centrality in terms of nodal degree and betweeness[5]. Figures 1 and 2 contain the network drawings of social life and academic life based on centrality and academic performance. Because of confidentiality of individual information, in the network drawing, a randomly assigned numbers instead of name were used to represent each node. The size of the point represents node degree and colors show different levels of performance. Based on the performance index that we designed in section 3, students' performance is categorized into three classes: low level is colored in red, medium level in blue and high level in black[6].

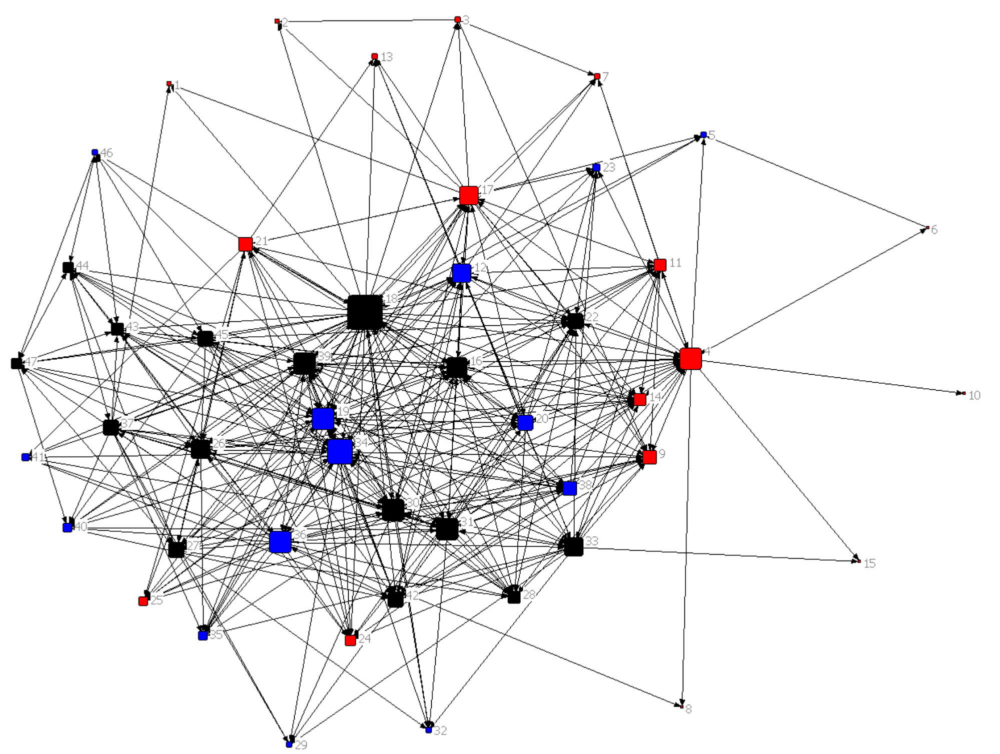
Figure 1 Social life network based on Centrality (node degree), academic performance



[5] On the one hand we found by using UCINET 6 that there is just one component in every network at frequency 1 so that focusing on local centrality is sufficient. On the other hand, by looking at betweeness it is possible to explore the effect of centrality in terms of broker/gatekeeper on performance.

[6] the performance value that is equal or lower than 0.8 is labeled as low performance; values between 0.8 to 1.04 are considered as medium; and high level of performance is larger or equal than value 1.04. We have specified this values in such way that each color is assigned to one third of the students.

Figure 2 Academic network based on Centrality (node degree), academic performance



Accordingly from the network pictures, people with high performance are more central in the network (with a high nodal degree). Therefore, we may hypothesize that *the more central a node is, the higher performance it might be.* Moreover, it can be observed that there are a certain number of nodes that have higher nodal degree but performing not very well. Thus, we predicted that there *might exist* a reversed U-shaped relationship between network centrality and academic performance[7].

H1: Social life Network centrality is positive related with Students' academic performance

H2: Academic life Network centrality is positive related with Students' academic performance

H3: Social life network centrality is inverted-U associated with students' academic performance

[7] The same results are found using betweeness in the appendix figure 1A and 2A

H4: Academic life network centrality is inverted-U associated with students' academic performance

From the network pictures above and below (also in appendix), we can see that the senior PhD students is close to the network centrality, however, some senior students who belong to the oldest batch show up a lower nodal degree. Therefore, we hypothesize that

H5: Student batch is inverted-U related with students' network centrality both in academic and social life connection

In order to estimate these hypotheses, we firstly used network analysis in terms of network centrality map drawing, Reachability to ego-network, and network density. Afterwards, we used OLS Regression model to make the confirmation.

4. RESULTS

4.1. Network drawing

Figure 3 shows strong interaction among students in the academic help network. We found that students are intended to seek for help from others who are in the same batch. Social life and Academic networks show the same result in terms of batch as well (see appendix figures 3A, 4A).

Figure 4 shows Life help network based on centrality and time of PhD study living in Maastricht. Colors represent the time students stay in Maastricht (red: below 50% of time, black: between 50% and 75%, blue: more than 75%). It is clear that people living in Maastricht more than 75% of time are more centralized (high nodal degree). This is an expected result that students seek for help from other students who are physically available to interact.

Moreover, all the network drawings show that people who have higher nodal degree (located closer to the center) typically belong to older batches (2005 and 2006 PhD batches). This is to say, interaction in the network is denser for senior batches. This result is sensible because people that have been in the PhD program for longer periods have had more chances to interact with other students.

Figure 3 Academic help network based on Batch

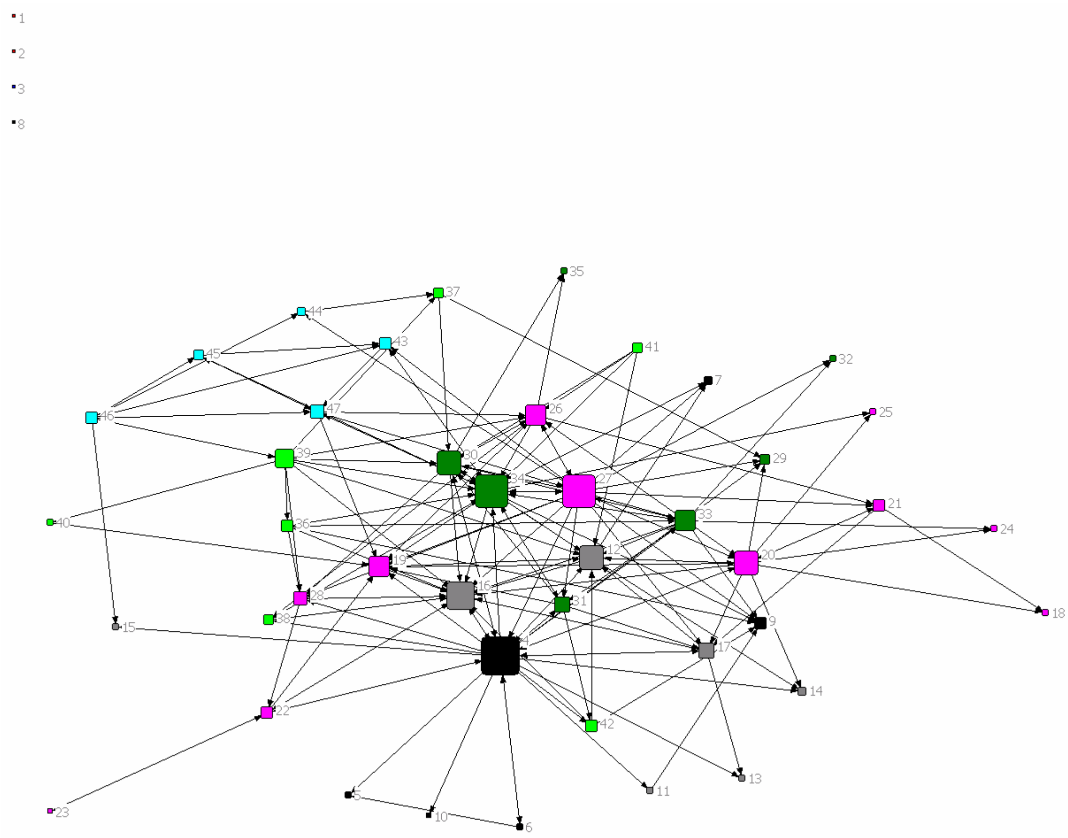
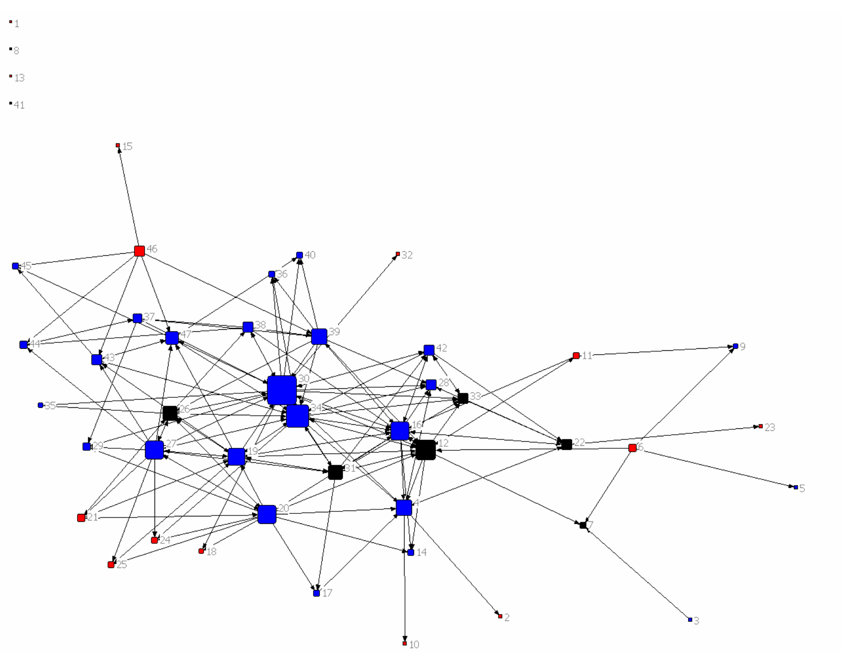


Figure 4 Life help network based on centrality and time living in the Maastricht.

(color red=1, blue=3, black=2)



Consequently, we primarily concluded that (1) central nodes are relatively similar in terms of students attributes in all networks; (2) people in the center enjoy higher level of academic performance, however it might not be true if expressed reversely; (3) to a large extent, students batch has positive relation with the nodal degree (network centrality), (4) intensive interaction occurs horizontally at the same batch; (5) interaction at academic and social life level took place amongst people who live in Maastricht more than 75% of time per year.

4.2 Reachability to ego-network

Forty-seven PhD students were incorporated as actors in our network analysis. We computed the descriptive statistics of size, density, average geodetic distance for each target that we assume as the center of ego-network. Seen from the result in table 2, the average size of ego-network is 24 and average density is 57%, which implies UNU-MERIT PhD students were acting in a relatively dense network.

The maximum size of the ego network is 43 which is quite close to an entire population ego-network, and by less than 3 steps every student can reach each other. These results show that students who had above-average size of ego network were the people who lived in Maastricht more than 75 % of time. Readers can refer to appendix Table 3A for detailed information.

Table 2 Ego-Network

	Size	Ties	Density	Avg. Dis.
max	43	583	100	2.94
min	2	2	1	1
average	24.085	294.611	57.058	1.43
SD	10.642	198.73	33.874	0.683

4.3 Network Density

Network density shows the proportion of possible lines that are actually present. This is important since we can estimate the extent to which PhD students at UNU-MERIT interact from different perspectives. We computerize the network density based on the formula $\Delta = \frac{L}{g(g-1)/2}$, where L represents the number of interactions exactly present and g stands for number of nodes in the network. The density of a network is assumed as 0 if there are no lines present and as 1 if all possible lines are present. From Table 4A in the appendix we can see that *PhD students interacted much more often in the social life than they did in the academic area.* Academic and life help networks present the lowest density, which might be because people would like to seek help from the closest social life friends.

4.4 Econometric Results.

One of the main purposes of this study was to explore the relationship between the degree of network connections and academic performance at the PhD student level. For this purpose, OLS Linear Regression Model was used. Two indicators were set as dependent variable separately: betweeness and nodal degree. We explored the relationship between social networks and academic performance as well as the relation between academic networks and academic performance.

Table 3 Effect of Centrality (nodal degree) in the *social life network* on the academic performance

Dependant variable: Academic performance index.

VARIABLES	(I)	(II)	(III)	(IV)
Degree (Social life Network)	0.0173***	0.0186***	0.0161***	0.00970*
	(0.00587)	(0.0053)	(0.00522)	(0.00516)
Degree squared (S. L.Network)	-0.000118**	-0.000131***	-0.000116***	-0.0000634[8]
	(0.0000452)	(0.0000409)	(0.0000399)	(0.0000399)
Weekly hours of work		0.0142***	0.0142***	0.0117***
		(0.00422)	(0.00406)	(0.00377)
Research group 1 dummy			-0.626**	-1.481***
			(0.295)	(0.381)
Age				-0.0247***
				(0.00783)
Constant	0.341**	-0.232	-0.144	0.893**
	(0.163)	(0.225)	(0.22)	(0.385)
Observations	47	47	47	47
R-squared	0.177	0.349	0.412	0.527

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

[8] Significant at p<0.12

The estimation results were put in Table 3, from which we can see the impact of node's social network degree over academic performance is significantly positive and its effect on academic performance decreases marginally as degree increases. We introduced several control variables in different specifications. In model (II) we introduced weekly hours of work. The result indicates a positive and significant impact. In model (III) we introduced a dummy variable---research group, being one if the student belongs to the specific area of research "Micro-based evidence research on innovation and technological change" and zero otherwise. Four other group dummies were introduced separately and together in additional regressions, which we did not show in the paper. Model (IV) is the complete model with all variables.

Table 4 incorporates the results associated with academic network. In accordance with the methodology used in table 3, academic network degree affects academic performance positively and significantly. The marginal effect is found similar to the results of social life network----marginally decreasing.

Table 4 effect of centrality (nodal degree) ***in the academic network*** **on the academic performance**

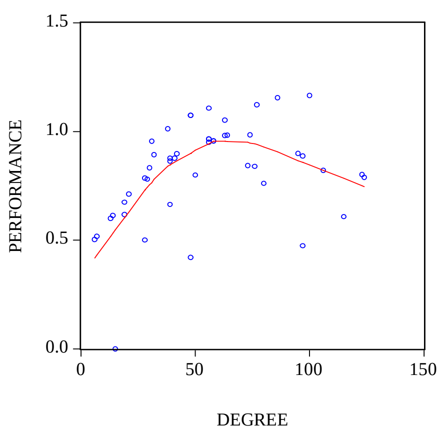
Dependant variable: Academic performance index.

VARIABLES	(I)	(II)	(III)	(IV)
Degree (Academic Network)	0.0228***	0.0255***	0.0221***	0.0170***
	(0.0077)	(0.00688)	(0.00677)	(0.0062)
Degree squared (A. Network)	-0.000276**	-0.000330***	-0.000295***	-0.000222**
	(0.000104)	(0.0000936)	(0.0000911)	(0.0000838)
Weekly hours of work		0.0152***	0.0152***	0.0127***
		(0.00425)	(0.00407)	(0.0037)
Research group 1 dummy			-0.638**	-1.474***
			(0.291)	(0.354)
Age				-0.0247***
				(0.00712)
Constant	0.500***	-0.107	-0.0384	0.914***
	(0.12)	(0.2)	(0.194)	(0.324)
Observations	47	47	47	47
R-squared	0.169	0.36	0.426	0.556

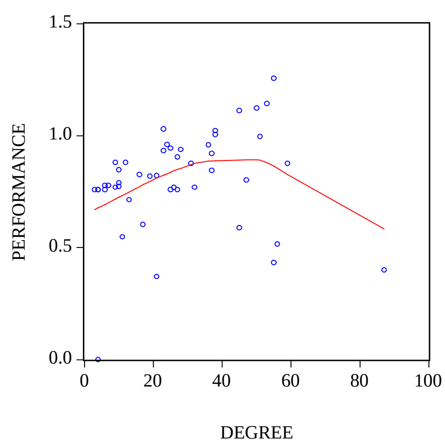
Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Since betweeness is able to reflect the effect of network broker on the student academic performance, we made estimation by using betweeness as independent variable. The result which can be seen in Tables 1A and 2A in the appendix shows *that betweeness of social life network and academic network also has a positive and marginally decreasing effect over academic performance*. The values of the parameters do not differ much from those found in table 3 and 4. Graphs 1 and 2 show the occurrence of estimated performance based on network centrality (in terms of nodal degree and betweeness). The results show that the relation between network centrality and students' academic performance has a reversed U-shape. This means that for very high levels of nodal degree, further degree increments lead to lower academic performance. The same exercise using betweeness as degree measure has the same results which can be found in appendix Graphs 1A and 2A.

Graph 1- Effect of centrality (nodal degree) in social life network on academic performance



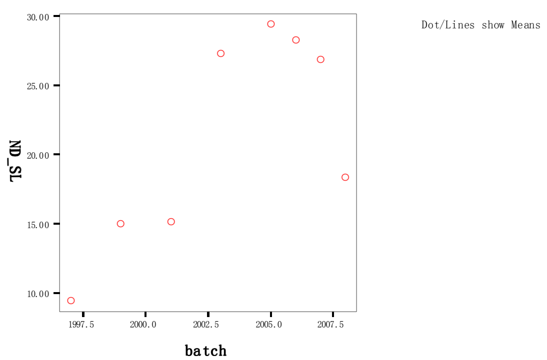
Graph 2- Effect of centrality (nodal degree) in academic network on academic performance



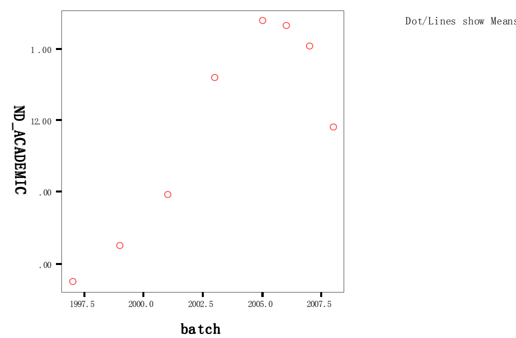
Therefore, we conclude that hypotheses 1, 2, 3, and 4 are sufficiently supported.

In order to estimate hypothesis 5, the data was processed again to draw an interactive dot graph. From graph 3 and 4 we can see that *hypothesis 5 of a reversed U-shaped relation between centrality and batches is supported*. We argued this is sensible because the senior students have more opportunity to interact with others. The marginal decreasing effect can be explained by the fact that the oldest batches spend more time on their thesis writing instead of social and academic interactions. We found that students who continue their PhD studies more than four years are more likely involved in other networks rather than UNU-MERIT. Therefore, hypothesis 5 is sufficiently supported.

Graph 3 Reversed U-shaped relationship between batches and Centrality in the social life network



Graph 4 Reversed U-shaped relationship between batches and Centrality in the academic network



4.5 Pearson correlation of centrality in 4 networks

In order to find the correlations of centrality (nodal degree) among four networks, 12 pairs of Pearson correlations were explored. From table 5 it can be seen that centrality in terms of nodal degree in 4 different networks (social life, academic, academic help and life help) are positively and significantly correlated, which means that people who are in the center of one network are more likely to be central in the other three networks.

Table 5 Pearson Correlation between centrality of social life network, academic network, Life Help network and Academic Help network

		Social Life	Academic	Life Help	Academic Help
Social Life	Pearson Correlation	1	.901(**)	.689(**)	.724(**)
	Sig. (2-tailed)		.000	.000	.000
	N	47	47	47	47
Academic	Pearson Correlation	.901(**)	1	.621(**)	.636(**)
	Sig. (2-tailed)	.000		.000	.000
	N	47	47	47	47
Life Help	Pearson Correlation	.689(**)	.621(**)	1	.852(**)
	Sig. (2-tailed)	.000	.000		.000
	N	47	47	47	47
Academic Help	Pearson Correlation	.724(**)	.636(**)	.852(**)	1

	Sig. (2-tailed)	.000	.000	.000	
	N	47	47	47	47

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

5. CONCLUSIONS

In this study, we aimed to identify the relationship between network centrality and network actors' performance. We specifically put our eyes on UNU-MERIT PhD students education program and made up five hypotheses based on the primarily network snapshots. The data was obtained from survey in Dec.2008 at UNU-MERIT and the combination of network analysis and econometric analysis successfully supported five hypotheses.

We took network analysis at four different levels: social life, academic, life help, and academic help. Four restricted econometric models and one complete econometric regression were applied in each network. Overall, we found that there does exist a reverted U-shaped relationship between network centrality and student's working performance; and student's batch is inverted U-shaped associated with his/her network centrality position. Additionally, we identified that weekly working hours have a positive and significant effect on performance, while student's age has a negative and highly significant effect on the same variable.

This paper firstly significantly contributes to studies on the peer-effect from methodological approach perspective. It combined elements of network analysis and econometric theories to set up and testify research hypothesis. Moreover, this study confirms that different measurements of network centrality do not have large variance when identifying its impact on performance. Finally, this paper contributes to the empirical studies that aim to understand the determinants of education. Since high quality education is one of the main pillars of development and social stability both in developed and developing countries and it is in the context of this fact that analyzing the determinants of students' academic achievements is a priority for multiple governments around the world, our findings offer a series of valuable hints to disentangle the highly complex education quality and students' performance.

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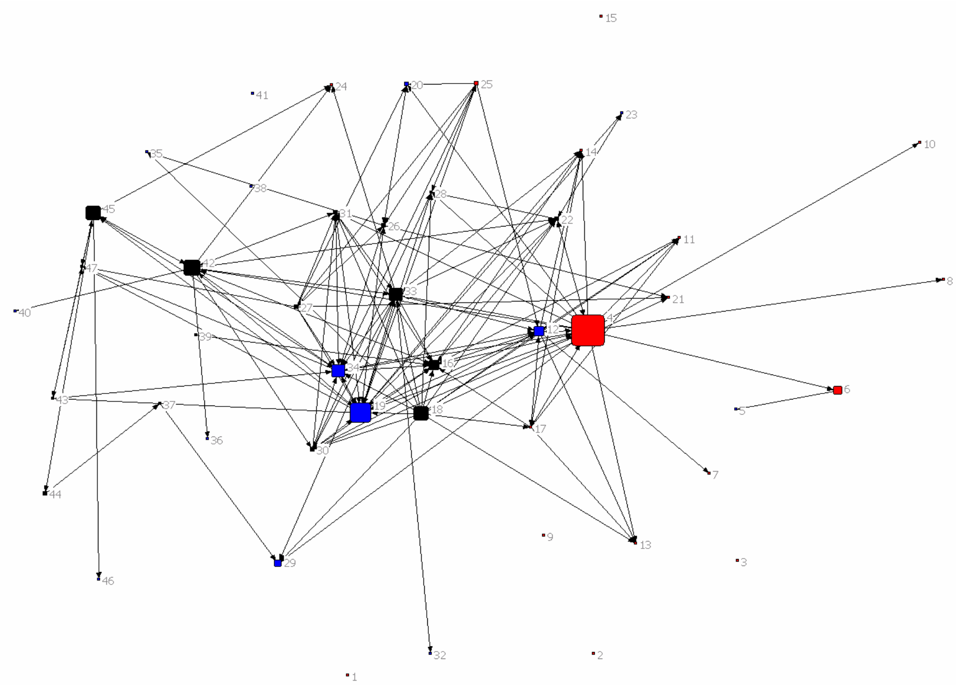
APPENDIX

Figure 1A Social life network based on centrality (betweeness) and academic performance



Appendix 2A. Academic network of strong tie based on Centrality (betweeness) and academic performance

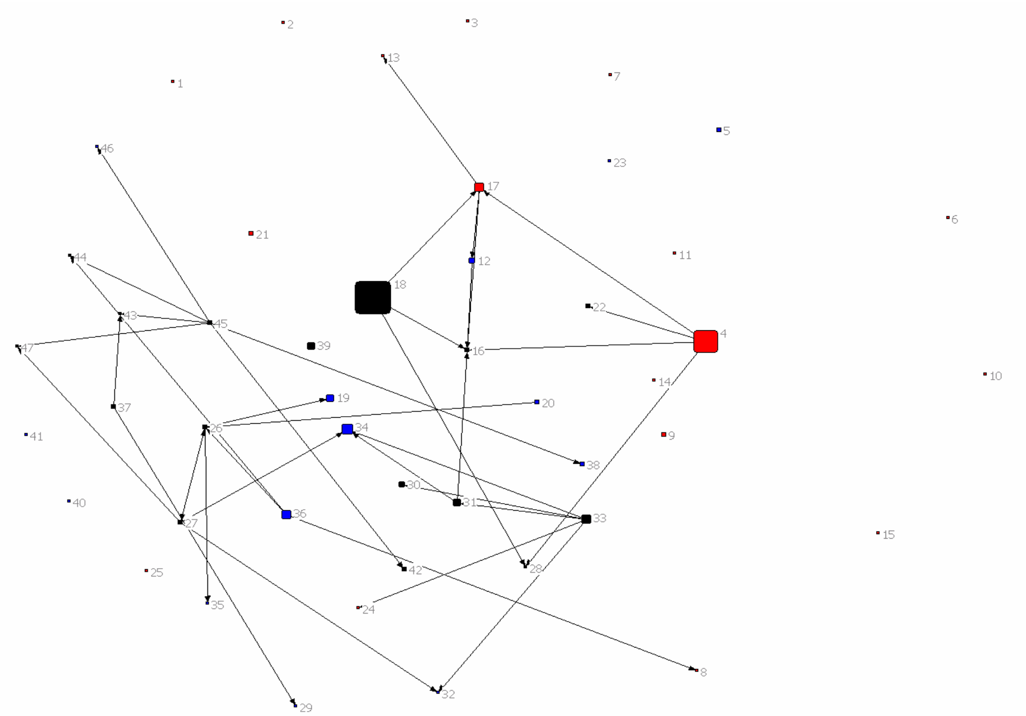


Figure 3A Social network of strong ties based on Batch

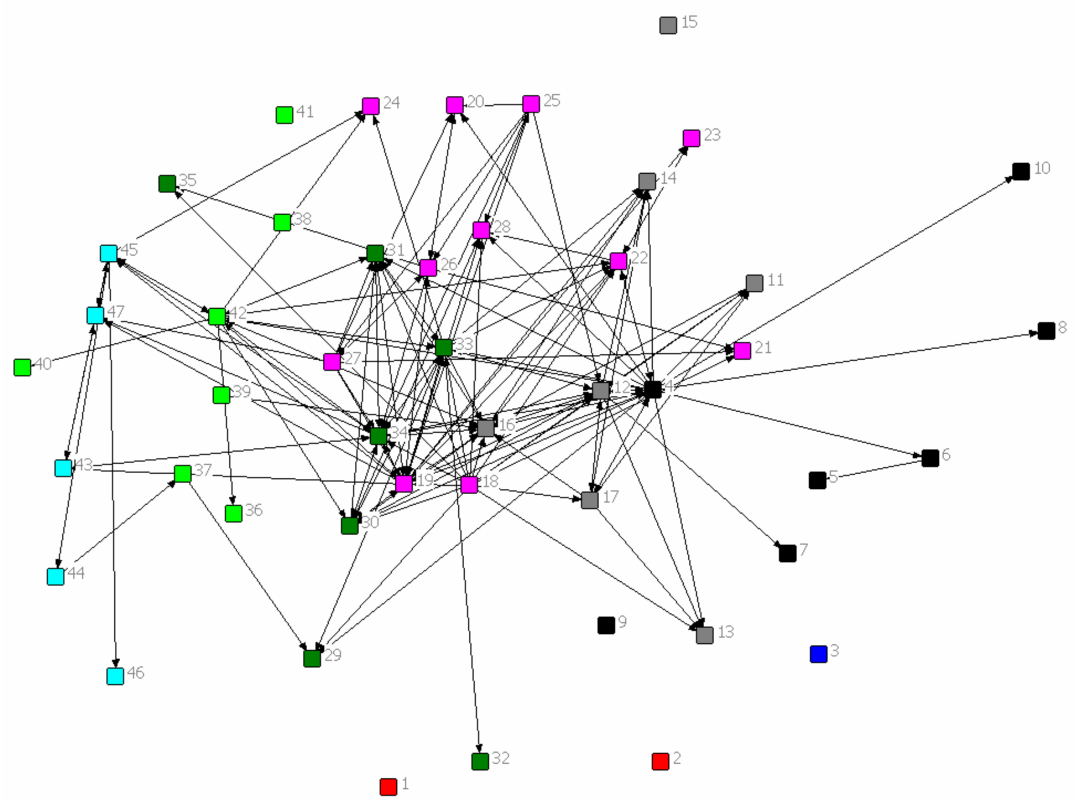


Figure 4A Academic network of strong ties based on centrality and batch

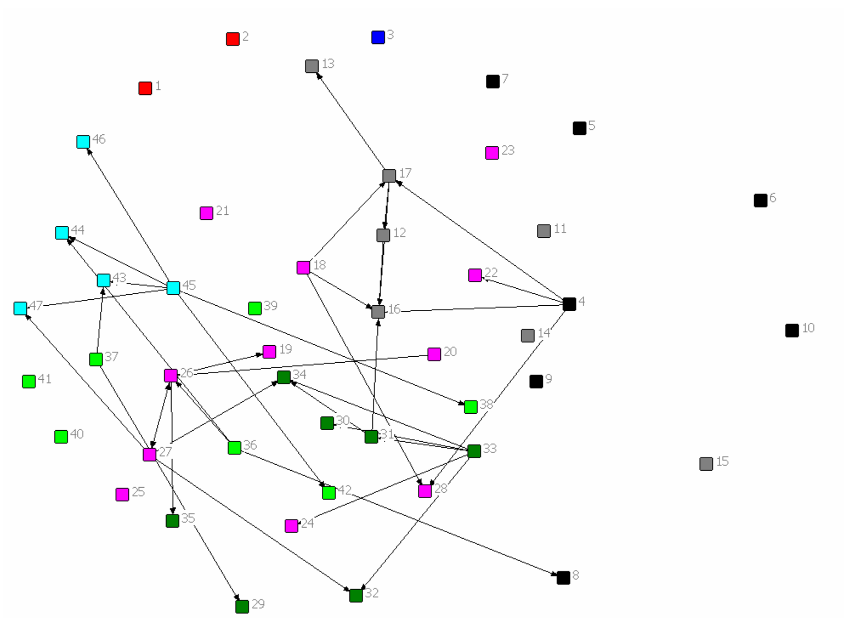


Table 1A The effect of betweeness in social life network on academic performance

Dependant variable: Academic performance index.

VARIABLES	(I)	(II)	(III)	(IV)
Betweeness (Social life Network)	0.0177***	0.0153***	0.0135**	0.0103**
	(0.00585)	(0.00564)	(0.00535)	(0.00483)
Betweeness squared (S.L. Network)	-0.000224***	-0.000189***	-0.000172**	-0.000121**
	(0.0000703)	(0.0000682)	(0.0000645)	(0.0000589)
Weekly hours of work		0.0109**	0.0111**	0.00983**
		(0.0045)	(0.00424)	(0.00377)
Research group 1 dummy			-0.759**	-1.614***
			(0.295)	(0.356)
Age				-0.0262***
				(0.0074)
Constant	0.717***	0.302	0.327*	1.230***
	(0.0652)	(0.182)	(0.171)	(0.297)
Observations	47	47	47	47
R-squared	0.188	0.285	0.383	0.527

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2A the effect of betweeness in academic network on the academic performance

Dependant variable: Academic performance index.

VARIABLES	(I)	(II)	(III)	(IV)
Betweeness (Academic Network)	0.00813**	0.00724**	0.00639**	0.00594**
	(0.00304)	(0.00285)	(0.00269)	(0.00232)
Betweeness squared (A. Network)	-5.53e-05***	-5.05e-05**	-4.63e-05**	-4.02e-05**
	(0.0000202)	(0.0000189)	(0.0000178)	(0.0000154)
Weekly hours of work		0.0123***	0.0125***	0.0103***
		(0.00445)	(0.00418)	(0.00364)
Research group 1 dummy			-0.776**	-1.670***
			(0.296)	(0.34)
Age				-0.0279***
				(0.00703)
Constant	0.732***	0.266	0.290*	1.269***

	(0.0655)	(0.179)	(0.168)	(0.286)
Observations	47	47	47	47
R-squared	0.148	0.276	0.378	0.551

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3A Reachability to ego-network

	Size	Ties	Densit	AvgDis
1	10	71	78.89	1.23
2	9	64	88.89	1.11
3	15	97	46.19	1
4	38	588.001406.00	1	2.63
5	15	166	79.05	1.21
6	13	63	40.38	1
7	15	169	80.48	1.2
8	3	6	100	1
9	20	290	76.32	1.24
10	2	2	100	1
11	26	360	55.38	1
12	38	619.001406.00	1	2.63
13	15	172	81.9	1.18
14	24	413	74.82	1.25
15	10	78	86.67	1.13
16	43	761.001806.00	1	2.33
17	35	544.001190.00	1	2.86
18	42	741.001722.00	1	2.38
19	39	707.001482.00	1	2.56
20	25	423	70.5	1
21	25	383	63.83	1
22	28	472	62.43	1
23	19	272	79.53	1
24	24	442	80.07	1.2
25	24	375	67.93	1
26	34	613.001122.00	1	2.94
27	32	583	58.77	1
28	31	565	60.75	1
29	18	273	89.22	1.11

30	38	660.001406.00	1	2.63
31	34	607.001122.00	1	2.94
32	10	89	98.89	1.01
33	39	713.001482.00	1	2.56
34	40	725.001560.00	1	2.5
35	19	290	84.8	1.15
36	29	494	60.84	1
37	28	483	63.89	1
38	31	573	61.61	1
39	31	546	58.71	1
40	17	252	92.65	1.07
41	24	369	66.85	1
42	28	479	63.36	1
43	20	282	74.21	1
44	14	162	89.01	1.11
45	23	366	72.33	1
46	11	102	92.73	1.07
47	24	380	68.84	1

Size: size of ego

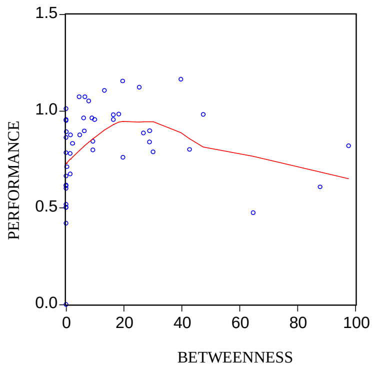
Tie: number of directed ties

AvgDist: average geodesic distance

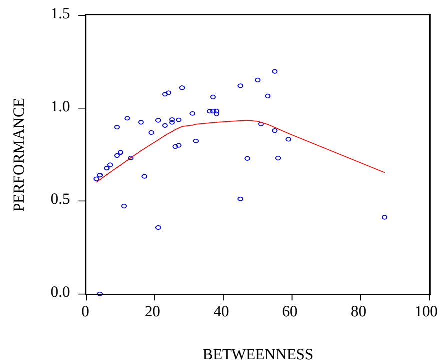
Table 4A network density

	Ava Value	Std Dev	No. of ties
Social life	0.8737	1.2887	
Academic	0.3686	0.8718	
Life help	0.0722		156
Academic help	0.0763		165

Graph 1A- Effect of centrality (betweeness) in social life network on academic performance



Graph 2A- Effect of centrality (betweeness) in academic network on academic performance



Questionnaire of networking analysis for UNU-MERIT PhD researchers

How old are you?	
During your PhD at MERIT,what percentage of your time have you spent in Maastricht?	
On average how many hours do you dedicate to your PhD research per week?	
How do you consider your PhD research according to the four-year PhD schedule and your supervisor's approval?	delayed ☐ on time ☐ ahead ☐
How many articles in peer-reviewed journals have you already published or submitted?	
How many UNU-MERIT working papers have you already produced?	
How many research-related contacts with your supervisor do you have per month(either by email or face to face)?	0 or 1 ☐ 2 to 3 ☐ >3 ☐

Do you have formal training before you came UNU-MERIT in:

Antropology or other social sciences	☐
Engineering	☐
Economic	☐
Management	☐
Others: please indicate	☐

In which category is your PhD research topic?

1. Micro-based evidence research on innovation and technological change	☐
2. The role of technology in growth and development	☐
3. Knowledge and industrial dynamics	☐
4. Innovation, global business strategies and host country development	☐
5. The governance of science technology and innovation	☐

Please answer the following questions in a scale from 0 to 4 (**0=nothing**, **1=low**, **2=medium**, **3=high** **and 4=very high**)

To what extent do you participate on a regular basis in academic seminars at UNU-Merit or any other research institution?

☐ ☐ ☐ ☐ ☐

To what extent is your previous research related to your PhD research?

☐ ☐ ☐ ☐ ☐

Now please answer the following questions in a scale from 0 to 4 (0=nothing, 1=low, 2=medium, 3=high and 4=very high)

You do not need to answer regarding the students with whom you have not interacted, we will assume a 0 value for these cases

Name	Friendship: How much have you socialized with this person (consider non-working related communication either in internet or face to face)?						Academic relationship: To what extent have you interacted with this student regarding to research?						when you need help, who of these students do you primarily prefer to ask?	
	0=nothing	1=low	2=medium	3=high	4=very high		0=nothing	1=low	2=medium	3=high	4=very high		Academic	Life
Ali	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Franco	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Norman	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Minh	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Abraham	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Bertha	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Márcia	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Ngoc	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Sandra	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Saurabh	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Teresa	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Ekin	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Fernando	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Francisco	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Marion	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Nils	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Semih	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Yoseph	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Alexis	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Asel	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Donatus	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Evans	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Ezequiel	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Jan Philip	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Lina	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Radhika	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Sergey	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Tina	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Zakaria	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐

Bilal	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Daniel	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Flavia	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Ivan	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Nora	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Shuan	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Than	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Anant	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Baseer	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Conrad	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Ibrahim	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Jun	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Kirsten	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Lilia	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Iman	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Muhammad	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Rodolfo	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Salih	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐
Ying	☐	☐	☐	☐	☐		☐	☐	☐	☐	☐		☐	☐

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