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Heterogeneity, incomplete information and efficiency: a longitudinal study of a students' network

Aditya Sekhar Das
Presidency University

Arya Gangopadhyay
Presidency University

Zakir Husain
Economics Department, Presidency University

Abstract

There is a considerable body of evidence showing that ties between actors are not random but are formed endogenously to maximise individual benefits. Such preferential attachment may be difficult if information is incomplete; in such cases, repeated interaction with the same set of agents may facilitate the identification of actors with whom forming ties is beneficial. The present study examines the formation of ties in a heterogeneous community characterised by incomplete information about the endowments of actors. Data was obtained through an online survey from students enrolled in the post-graduation programme in the department of Economics, Presidency University, and analysed using social network analysis tools and concepts. Results revealed that, over time, the density, reachability and connectivity of the network increased. Greater interaction among actors facilitated the identification of high value actors, and led to an efficient and stable network—but at the cost of polarisation within the network. The study concludes by arguing the need to supplement the analysis of efficiency and stability with an enquiry into the normative implications of polarisation.

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Contact: Aditya Sekhar Das - aditya.das002@gmail.com, Arya Gangopadhyay - gangopadhyayarya@gmail.com, Zakir Husain - dzhusain@gmail.com.

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1. Introduction

Social network analysis refers to the study of interpersonal relationships. It is formally defined as a collection of nodes (actors) linked by several relationships indicated by uni-directional or bi-directional ties. Network structures have been widely examined to study ties between job market applicants (Granovetter 1983; Granoveter 1994), heart patients (Fowler and Christakis 2009), terrorists (Krebs 2002), migrants (Garip 2008; Munshi 2011), cyberbullies (Barlett et al. 2018), and telecommunication firms (Barnett 2001), and so on. Now ties between heterogeneous actors may be formed randomly or endogenously. There has been extensive research on preferential attachment (Jackson 2005; Jackson and Rogers 2007), based on either attributes (Bourdieu 1984, 1988; McPherson, Smith-Lovin, and Cook 2001) or centrality positions in inherited networks (Joshi, Mahmud, and Sarangi 2020). The basis of tie formation and the resultant network structure will depend upon the context and the nature of incentives from exchange (Burger and Buskens 2009; Jackson and Xing 2014).

Now actors may differ from each other (Goldsmith-Pinkham and Imbens 2013) so that their effects on outcomes will vary. When actors possess perfect information about peers, self-selection of peers is relatively easy (Bala and Goyal 2000; Jackson and Xing 2014; Johnson et al. 2009). Incomplete information about peers may, however, hinder the process of tie formation (Goeree, Riedl, and Ule 2009). In such cases, repeated interaction may allow actors to obtain information about peers (Roth and Schoumaker 1983; Chen et al. 2014). Studying such dynamic interaction is not easy and has been undertaken mainly in either networks with pre-existing or endogeneously formed ties. Practical difficulties have limited the study of the origin of networks and interaction till the cessation of interaction. The present study examines the patterns of tie formation and its evolution in a student network. The focus is on ties formed to seek academic assistance, and not for social interaction. The size of the network is constant over time, and interaction occurs over a period of three semesters. We show that ties are formed selectively, leading to the networks becoming more efficient over time. However, the increased efficiency comes at the cost of polarisation that may affect equity within the network.

The paper is structured as follows: Section 2 states the objective and hypotheses of this study; it is followed by a discussion of the data and method used in the study (Section 3). Section 4 presents the results, while the next two sections discuss the results and draws appropriate lessons from the study.

2. Materials and methods

2.1 Literature review

In recent years, the role of social processes in the formation of the study has become a growing area of research (Leung 2019). In their seminal study, Bala and Goyal (2000) have examined strategic tie formation in the presence of perfect information. It is an important area of research given the heterogeneity of actors (Goldsmith-Pinkham and Imbens 2013). While some studies have shown that differences in productivity levels among actors may lead to homophily (Jackson and Xing 2014; McPherson, Smith-Lovin, and Cook 2001), the presence of differences in the endowment of actors may also facilitate exchange and encourage heterophily (Rogers and Bhowmik 1970; Kimura and Hayakawa 2008; Johnson et al. 2009). In general, however, imperfect information, asymmetric linking opportunities and the presence of existing ties among some actors may constrain preferential attachment optimising individual pay-offs (Goeree, Riedl, and Ule 2009). Lacking information, actors joining a network may perform local searches in the neighbourhood of randomly met peers (Jackson and Rogers 2007). Alternatively, actors may rely on other cues for selecting peers (Kossinets and Watts 2009; C. Zhang et al. 2017; Biggs, Raturi, and Srivastava 2002; Biggs and Shah 2006); such focal play may lead to the evolution of cultures or conventions (Jackson and Xing 2014; Schelling 1960). A recent study reports that incomplete information may lead to the development of biased perceptions about potential peers, so that individual utility maximisation may lead to group segregation, reducing social welfare (Zhang & Carver, 2022). In dynamic games, however, repeated interaction enable agents to observe their potential peers over time and assess their productivity, trustworthiness and other relevant attributes; it enables actors to revise the assessment of which actors to form ties with (Roth and Schoumaker 1983; Chen et al. 2014). Star networks may develop in such situations, based on a single high value agent, with the centrality, stability and efficiency of the network increasing over time (Goeree, Riedl, and Ule 2009).

Existing studies on tie formation among heterogeneous actors with incomplete information are either based on a theoretical structure (Dutta and Jackson 2003; Jackson and Wolinsky 1996; Jackson 2010; Bala and Goyal 2000), or behaviour of agents in laboratory settings (Goeree, Riedl, and Ule 2009). Empirical studies based on the actual behaviour of communities are rare, and mostly use either an endogenously formed network (Sacerdote 2001), or large data sets containing information on existing ties (Patacchini, Rainone, and Zenou 2017; Chandrasekhar and Jackson 2018; Jain and Langer 2019; Jain and Kapoor 2015). In contrast, longitudinal studies of the formation of networks are rare because of the practical difficulties of studying networks over the entire duration of interaction. Fresh entry and attrition are other constraints (Greif 1989; Biggs, Raturi, and Srivastava 2002; Kali 1999).

2.2 Objective and hypothesis

The present study uses data collected from post graduate students in a single department of an Indian University to examine the evolution of ties formed for academic purposes over the first three semesters of the programme.[1] Studying student networks in non-residential academic institutions have some advantages. Given the short duration of the course, stability in network size, heterogeneity with respect to academic merit and availability of information about actors in initial stages of interaction,[2] the study of ties between students provide an opportunity to examine the interplay of heterogeneity and lack of information to examine the evolution of the network and its characteristics over time.

The present study argues that the absence of information about the productivity (in terms of academic merit) of each actor constrains optimal tie formation in the first semester.[3] Since there has to be some basis for choosing peers, ties will initially be formed on the basis of easily observed markers like the under graduate college (whether studied in the department of Economics, Presidency University, Kolkata, India). In this phase, class representatives will be the key players in the network. Subsequently, actors gain information about each other and ties will form on the basis of academic performance in the previous semester. High value actors will emerge with high centrality scores; they will compete with, and even displace, the class

[1] In the fourth semester students undertook projects, which limited their interaction; so ties in the last semester were not studied.

[2] Some students had studied in the University for their Bachelors programme; such individuals have inherited ties between themselves. The network also comprises actors who are strangers to each other as they have joined the University from other institutes.

[3] The lack of information is compounded by the online nature of interaction in the first semester. The difficulties of forming ties in online student communities has been discussed in Namhata et al. (Namhata et al. 2022).

representatives as the key players.[4] Simultaneously, given that academically strong students gain by interacting between themselves rather than with weaker students, polarisation is expected occur within the network. It will be reflected in increasing homophily.

The hypotheses of this study are:

(i) Over time the density, centrality, compactness and connectivity of the network will increase (H1);
(ii) Ties will be formed selectively, leading to polarisation and the emergence of marks based homophily (H2);
(iii) The number of high value actors will increase over time (H3); and
(iv) The network will become more efficient and stable over time (H4).

2.3 Data

The data was collected from students enrolled in the Masters of Applied Economics course of the Economics Department of Presidency University, Kolkata, in 2020. The post-graduate programme comprises four semesters over a period of two years. The first semester normally starts in July and ends in December. However, in 2020, the course started in January 2021 as a result of the Covid-19 pandemic. The first two semesters had to be completed within the first six months due to the delay in the academic schedule (they ran from January to March, and April to July). The third semester commenced in mid-August and continued until January 2022.

The data was collected using Google forms (given in Appendix), where the students were asked to report the names of their classmates whom they approached for academic help. Such data was collected after the end of each of the first three semesters to study the evolution of the network formed, and assess the corresponding changes in network positions for each of the actors. In addition, after informing the students, information about their gender, caste, religion, their undergraduate college (that is, whether from Presidency University, or elsewhere), Semester Grade Point Average (SGPA) obtained was extracted from the University records (admission forms and examination records). Informed verbal consent of the students were taken and the data anonymised. A briefing session was held with the students before circulating the Google forms to explain that the interaction on which information was sought related to both academic matters like timings of classes, reference material, dates of examination, and also on internship opportunities and job placement interviews.

The number of students was 21. The major proportion of the students were Hindus (86%), while about a half from general social groups (52%). The percentage of female respondents was 52%. or A large proportion had completed their undergraduate degree outside Presidency University (62%) (Table 1). The information was subsequently used to test for the basis of homophily.

Table 1: Sample profile

Characteristics	Number	Percentage
Gender		
Male	10	47.62
Female	11	52.38
Religion		

[4] The two class representatives were selected through a process of self-nomination, followed by voting by the students. Though not a rule, students were advised to select one representative from Under Graduate students of the University and another from new entrants to the institute.

Hindu	18	85.71
Muslim	3	14.29
Social category		
General	11	52.38
Disadvantaged	10	47.62
Under Graduate College		
Presidency University	8	38.10
Other universities	13	61.90

Source: Estimated from data

Some of the information disclosed was sensitive and the identity of the students had to be kept confidential. The class roll number was, therefore, recoded. We were initially studying two cohorts, the first cohort (admitted in 2019) was numbered 1-20, and the second cohort (enrolled in 2020, and whose behaviour is being studied in this paper) coded as 21-40. As the code numbers do not imply anything, we have retained the codes used.

2.4 Sample size and its implications

The group size is very small and is a major limitation of the work. At the same time, the small size of the group enabled us to study the **entire** group and follow them (and the evolution of the ties) over time. It would not have been easy to study a large group, comprising of (say) 100 students, and trace their networks over three semesters, particularly given the constraints imposed by the restrictions prevailing during the COVID pandemic.

The analysis has also not undertaken any statistical tests—except with respect to homophily (Table 3) and with respect to the change in change in mean rank of peers (Table 5). This requires some justification.

Firstly, a sample is a subset of the population. In the present case, we are studying the **entire network, and not some members**. In other words, we are studying the population – though the issue of generalization (whether the results apply to other groups) is an important question related to external validity of the results. So the standard statistical tests are not relevant. Secondly, as pointed out by Leung (2019), statistical tests in small networks are appropriate only under restrictive conditions. Finally, the specialized software used for the analysis of networks (UCINET) did not permit statistical tests except for the E-I index (Table 3). So we have not performed any statistical tests of significance to confirm the hypotheses.

2.5 Methodology

This study uses standard measures like degree, density, reachability, distance and centrality to capture the main network characteristics. Substructures within the network are analysed using the clustering coefficient and E-I index. Sociograms—visual depictions of ties linking actors in a network—are used to examine the nature of ties formed, particularly whether a star formation develops. They also identify key players. In addition, the centrality scores of each actor and their scores as hubs and authorities (Kleinberg 1999) are estimated. The efficiency of the network was analysed using the average of the mean ranks of egos of every actor. The stability of the network is examined using fragmentation, stability, and expansion ratios. These concepts are discussed below.

Network measures

The size of the network is indicated by the number of actors (or nodes) in the network. The total number of connections/ties each node has with other nodes determines its degree in a network. The density of a network is the ratio of the actual number of ties to the potential number of ties. The idea of a path is also used to represent the interactions between the actors. The path can be simply defined as the connection between two pairs of actors.

If reachability is high in a network, information will be transmitted throughout the network regardless of the point of its origin. An actor is "reachable" by another if we can trace a set of connections from the origin (i.e., the source) to the target actor, notwithstanding the number of actors in between them. However, even if an actor might successfully communicate with another, the connection between them may be weak. By weak ties we mean that there are few pathways connecting two actors. In such cases, actors have a low "connectivity," which means that there are few routes for information to travel from one actor to the next.

Connectivity calculates the number of nodes that would have to be removed to ensure that actor A cannot reach actor B. Mathematically, connectedness is equal to one minus fragmentation where fragmentation is the proportion of pairs of nodes that are unreachable. To capture the aspect of how the actors are embedded in the networks, the common approach generally employed is to examine the distance between the actors. If two actors are adjacent, then the distance between them is one. The distance among the actors is an important macro-characteristic of the network as a whole. The most commonly used definition of distance between two actors is called the geodesic distance. The geodesic distance is the shortest distance between two actors. The longest path is called eccentricity, with the largest eccentricity in the network being the diameter of the network.

Centrality measures

Centrality is a measure that determines the position of an actor in the network. A study of the centrality measures helps us assess the roles of different actors and identify their importance in the network. There different ways to measure centrality are discussed below:

Degree centrality is a measure of an actor's level of involvement or activity in the network. The formula for degree centrality, for actor i:

$$C_D(i) = \sum_{j=1}^{n} x_{ij} = \sum_{i=1}^{n} x_{ji}$$

when x_{ij} = value of the tie from actor i to actor j (value is either 0 or 1) and n = number of nodes in the network. In this case, we are measuring out-degree centrality which measures the number of alters an actor sought information from. It, therefore, determines the expansiveness of an actor in the network in terms of the number of ties he/she's giving. The equation for out-degree centrality for actor i:

$$C_0(i) = \sum_{j=1}^{n} y_{ij}$$

when y_{ij} is the number of ties actor i have with other actors j.

Eigenvector centrality helps us to explore the local network of actors immediately adjacent to our focal actor. It is measured by the sum of an actor's connections to the alters, weighted by their degree centrality. Rather than a formula, we make use of an algorithm to identify the largest eigenvalue of an adjacency matrix. Thus, $C_E(i)$ = the eigenvector centrality for actor i which is the i-th entry of the unit eigenvector e. Here e refers to the largest eigenvalue of the adjacency matrix.

Betweenness centrality deals with an actor's position in the entire network. It counts how many times an actor is placed on the geodesic, which is the shortest path linking two actors. The formula for betweenness centrality for actor k is:

$$C_B(k) = \sum \frac{\theta_{ikj}}{\theta_{ij}}, i \neq j \neq k$$

where,
θ_{ikj} = the number of geodesics linking actors i and j passing through the node k,
θ_{ij} = the number of geodesics linking actors i and j.

Closeness emphasises the actor's independence. It is measured as the distance between two actors. The formula for closeness centrality for actor i:

$$C_c(i) = \sum_{j=1}^{n} d_{ij}$$

where,
d_{ij} = distance connecting actor i to actor j.

The concept of Beta Centrality was developed to examine whether an actor gained power from his/her proximate contacts, or was it derived from the extensive network structure. The equation for beta-centrality is:

$$C_\beta(i) = \sum_{j=1}^{n} A_{i,j}(\alpha + \beta C_\beta(j))$$

where,
α = a scaling parameter, which is set to normalise the score,
β = a value selected by the analyst to reflect the amount of dependence of actor i's centrality on the centralities of the alters to whom actor i is directly tied. This must be smaller than the reciprocal of the largest eigenvalue,
$A_{i,j}$ = the adjacency matrix,
$C_\beta(j)$= the centrality of j, i.e. the centrality of actor i's partners.

Sub-structures

In most cases, actors interact with a very small group of other actors, many of whom know each other. In other words, they form "clusters". We can measure clustering in a graph by examining the local neighbourhood of an actor (i.e. actors directly linked to the ego) and calculating the density of that neighbourhood without the ego. We can then extend this process for all actors in the network, and then compute the degree of clustering as an average of all the neighbourhoods in the graph.

To calculate the overall graph clustering coefficient, first, the densities of the neighbourhoods of all of the actors are measured and then the average of all these densities is computed. On the other hand, the "weighted" version provides weights to the neighbourhood densities in proportion to their size. In other words, actors with larger neighbourhoods get more weight while calculating the average density. Since larger graphs are generally (but not necessarily) less dense than smaller ones, the weighted average neighbourhood density (or clustering coefficient) is usually less than the unweighted version.

Simple groups (actors with ties between them) evolve over time into more complex ones. Cliques are the (maximal) subgraphs of nodes that have all possible ties present among themselves. Generally, actors are considered to be a member of a clique if they are related to every other member of the group at a distance greater than one. A path distance of two is usually employed. This is the same as "a friend of a friend." This strategy for defining substructures is known as an N-clique, in which n stands for the maximum length of pathways to all other members.

To see whether the actors form clusters based on a particular attribute or form the clusters randomly, we study a measure known as *homophily*. It refers to a social situation in which an actor prefers to interact with actors belonging to the same group, or who exhibit a similar attribute. Homophily is measured using the External-Internal (E-I) index:

$$\text{E-I Index} = (T_E - T_I)/(T_E + T_I),$$

where, T_E = the number of external ties; T_I = the number of internal ties.
In the E-I index, we subtract the number of ties to other group members (T_I) from the number of ties of group members to outsiders (T_E) and divide this by the total number of ties (T_E+T_I). The index value ranges from -1 to +1. A value close to -1 depicts homophily (actors prefer interacting with members within the group), while a value closer to +1 indicates heterophily (actors interact more with members outside the group). Values closer to 0 mean that the ties have been formed randomly.

Dynamic changes
Using the EGONET function in UCINET we obtained information on the following:

(i) New Ties: Number of new ties added in the second period
(ii) Lost Ties: Number of lost ties that were present in the first period and not in the second
(iii) Kept Ties: Number of ties present in both the periods
(iv) Never Ties: Number of ties absent in both the periods

To study the evolution of ties among the actors in the network, and the evolution of the complete network in general, we calculated the stability ratio using the formula:

$$\text{Stability Ratio} = \frac{Kept\ Ties}{Number\ of\ ties\ in\ the\ previous\ semester}.$$

Another estimated ratio indicating the change in the network is the expansion ratio, defined as:

$$\text{Expansion ratio} = \frac{(New\ ties\text{-}Lost\ ties)}{Number\ of\ ties\ in\ the\ previous\ semester}.$$

3. Findings

3.1 Network measures

The network measures are reported in Table 2. The number of nodes was 21, implying a potential 420 ties between the actors. The number of ties, density and average degree of the network had increased consistently over the three semesters, indicating increasing interaction. The rising degree centrality indicated an increase in tie-formation between actors over the study period. The closeness measure was higher in Semester 3 compared to Semester 2; it implies faster dissipation of information in the network. Only betweenness centrality remained stable over the period of study. The network also became more compact and connected over time. The analysis, therefore, validates H1—density, degree centrality, compactness and connectivity of the network will increase. However, the conclusion is not based on statistical tests. Paradoxically, however, both the geodesic distance and the diameter had increased. Further, the proportion of actors within a distance less than three declined. It implies the possibility of clusters in the network.

Table 2: Network Measures

Measures	Semester 1	Semester 2	Semester 3
Number of nodes	21	21	21
Number of ties	74	84	94
Average degree	3.52	4.00	4.48
Density	0.18	0.20	0.22
Reachability			
Connectedness	0.78	0.91	0.91
Compactness	0.45	0.48	0.48
Fragmentation	0.22	0.10	0.10
Distance			
Average geodesic distance	2.00	2.39	2.60
Proportion within three	0.78	0.76	0.71
Diameter	4.00	7.00	7.00
Centrality			
Degree	0.28	0.32	0.35
Betweenness	0.40	0.40	0.40
Closeness	0.59	0.57	0.59
Clustering			
Overall graph clustering coefficient	0.49	0.24	0.34
Weighted overall graph clustering coefficient	0.24	0.22	0.27

Source: Estimated from data

3.2 Clustering and homophily

The overall graph clustering coefficient displayed a U-shaped trend (Table 2). After weighing for network size, however, we found that clustering had increased from 0.24 (Semester 1) to 0.27 (Semester 3).

A relevant question in this context relates to the possible basis for the formation of clusters. Attributes like gender, caste and religion turned out to be statistically insignificant in all semesters and are not reported. The E-I Index for undergraduate college (Table 3) indicated the presence of homophily only in Semester 1 (-0.186). In the first semester, students coming from different colleges were strangers entering into an unfamiliar environment and needed time to choose their egos. This led them to cluster together. In contrast, students of Presidency University were situated in a familiar environment and had already formed ties with their peers. Over time, however, the actors interacted between themselves online and through social media (like Facebook) and started forming ties. In subsequent semesters, therefore, the E-I index became statistically insignificant.

To test for homophily based on academic performance, we calculated the median marks obtained by the students in the previous semester. In the case of semester 1, the final marks obtained in the University examinations were considered. Students were categorised into two groups— those who obtained marks above the median marks and those who secured marks below the median marks.[5] It was undertaken for each semester.

[5] We also used mean to classify students, but did not get any major difference in the classification. If measures like Q1 and Q3 had been used results would have been varied. Using central tendency based measures to divide students into roughly equal halves appears intuitively appropriate in the present context, particularly given the

Table 3 revealed the absence of a statistically significant level of marks-based homophily in semester 1 (E-I Index = 0.474). The undergraduate examination had been conducted on an online mode and the assessment process varied across institutions. So students reportedly felt that marks secured in the Under Graduate examination was not a reliable indicator of academic merit. In the second semester, when the assessment became uniform, the actors displayed marks-based homophily (-0.125), which increased further to (-0.135) in the third semester. The hypothesis that the observed index differs from zero was statistically significant at a ten and five per cent level, respectively, but not at a one percent level. It implies selective attachment among actors and polarisation based on academic performance, confirming H2.

Table 3: E-I index over semesters

Statistics	Semester 1	Semester 2	Semester 3
Under Graduate college			
Observed E-I index	-0.186	-0.094	-0.081
Expected E-I index	-0.01	-0.01	-0.01
Std. Dev.	0.116	0.108	0.096
Probability	0.074	0.274	0.263
Academic performance			
Observed E-I index	-0.051	-0.125	-0.135
Expected E-I index	0.048	0.048	0.048
Std. Dev.	0.085	0.097	0.087
Probability	0.171	0.052	0.027

Source: Estimated from data

In this context it should be pointed out that the paper-wise grades and semester grade point average of each student were posted on the Departmental noticeboard and was visible to all students. It facilitated the respondents to identify the peers who were academically strong and with whom ties could be formed. The availability of ready information about examination performance is an important factor affecting the formation of ties in students' networks. While such information is available in many South Asian universities, it may not hold in other contexts. Even if there is public disclosure of marks, the size of the group may be very large (Calcutta University or Delhi School of Economics, for example, has over 200 students in each year); it will also constrain identifying students with whom tie formation produces the most academic benefits. These two features (viz. small size of network and public disclosure of marks) will affect the external validity of the results; students' networks in Universities which do not possess such features may not display academic merit-based homophily, or do so to a much weaker extent.

3.3 Sociogram

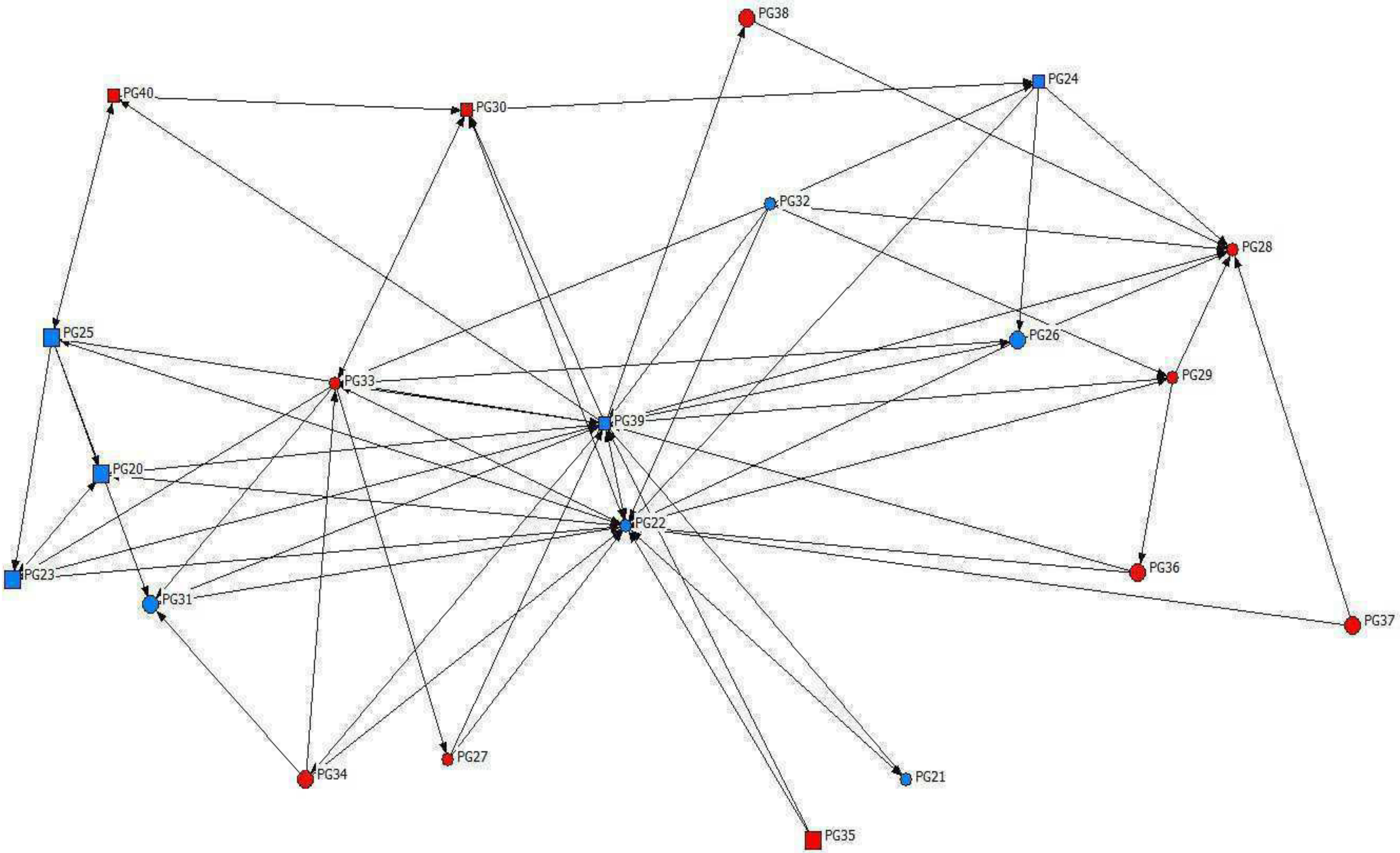
The sociograms depicting nature of interactions visually are given in Figures 1, 2 and 3. Following the standard practice, actors are distinguished by the colour, shape of nodes and its size. Thus, red indicates female and blue male students; circle denotes that the actor was a student of Presidency University at the under graduate level, while squares identifies students from other institutes who had been inducted at the Masters level in Presidency University. Finally, the size of the node indicates academic performance (students whose marks are greater

small size of the group. Moreover, students may not have perfect information on the academic merit of each student (as it varies over semesters), but they have a broad sense of the ranking within the class. So the use of a rank based method like median to assess the students appears intuitively justified.

than the median marks for that semester are identified by larger nodes vis-à-vis students whose marks was lower than median have smaller sized shapes). The direction of the arrows indicate who is being approached for information.

In Figure 1, we observe that the class representatives (PG22 and PG39) are two key players in the network. Connectivity appeared quite high. Even the actors at the periphery (PG28, PG37, PG35, PG21, PG27) were well connected and hade ties with the class representatives and with some other students.

Figure 1: Sociogram of the network in Semester 1

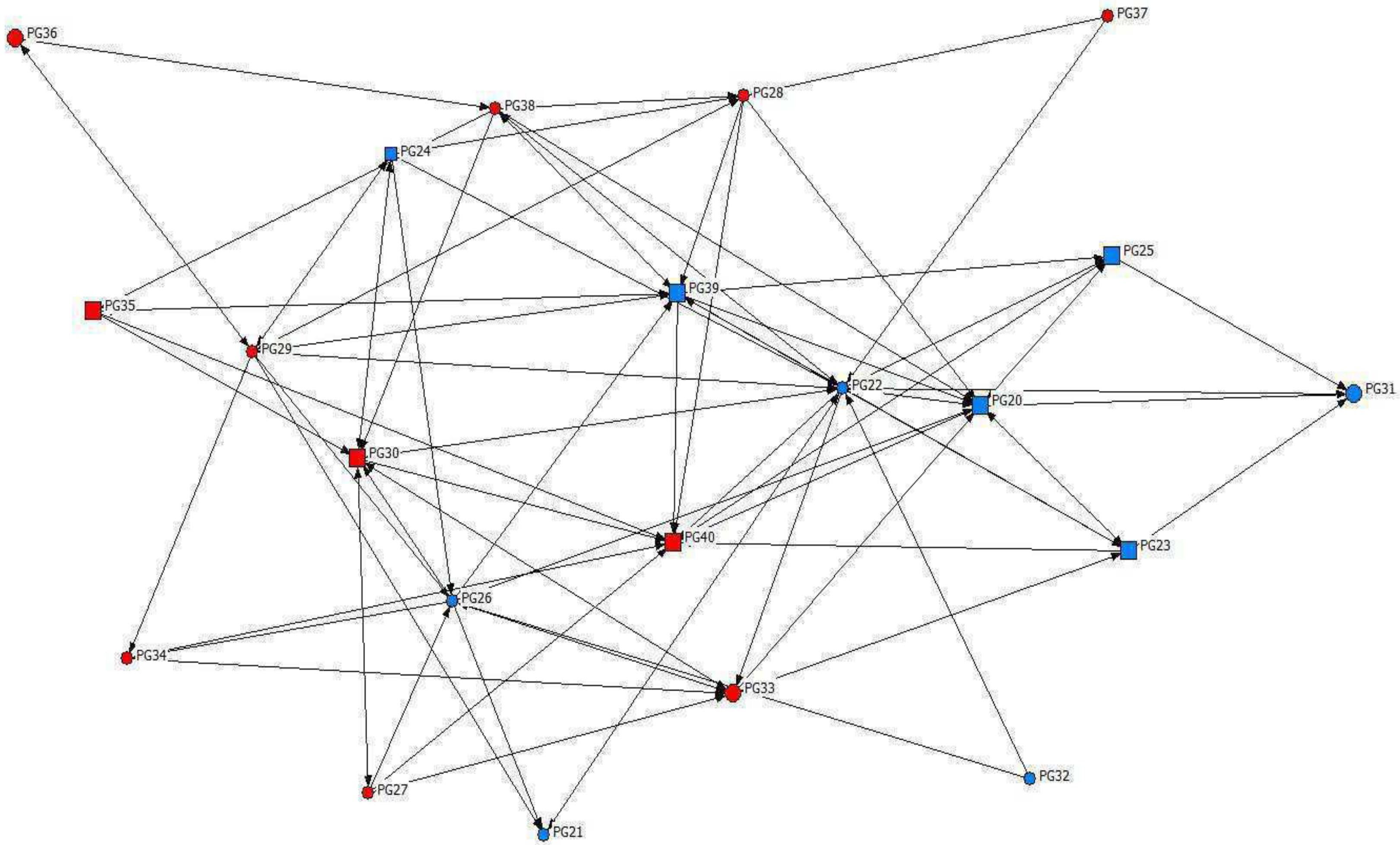


Source: Estimated from data

Figure 2 indicates an increase in connectivity between actors. Compared to semester 1, the density of the network had increased. The number of key players had increased each other from two to four—in this semester the key actors include the class representatives (PG22 and PG39) and two new actors (PG20 and PG40). Both these students were students of Presidency University at the undergraduate level, and were in the academically superior group. Although there were fewer people at the periphery of the network, the connectivity of those at the periphery seems to have reduced. For instance, PG32, PG37 and PG36 had only two direct connections each.

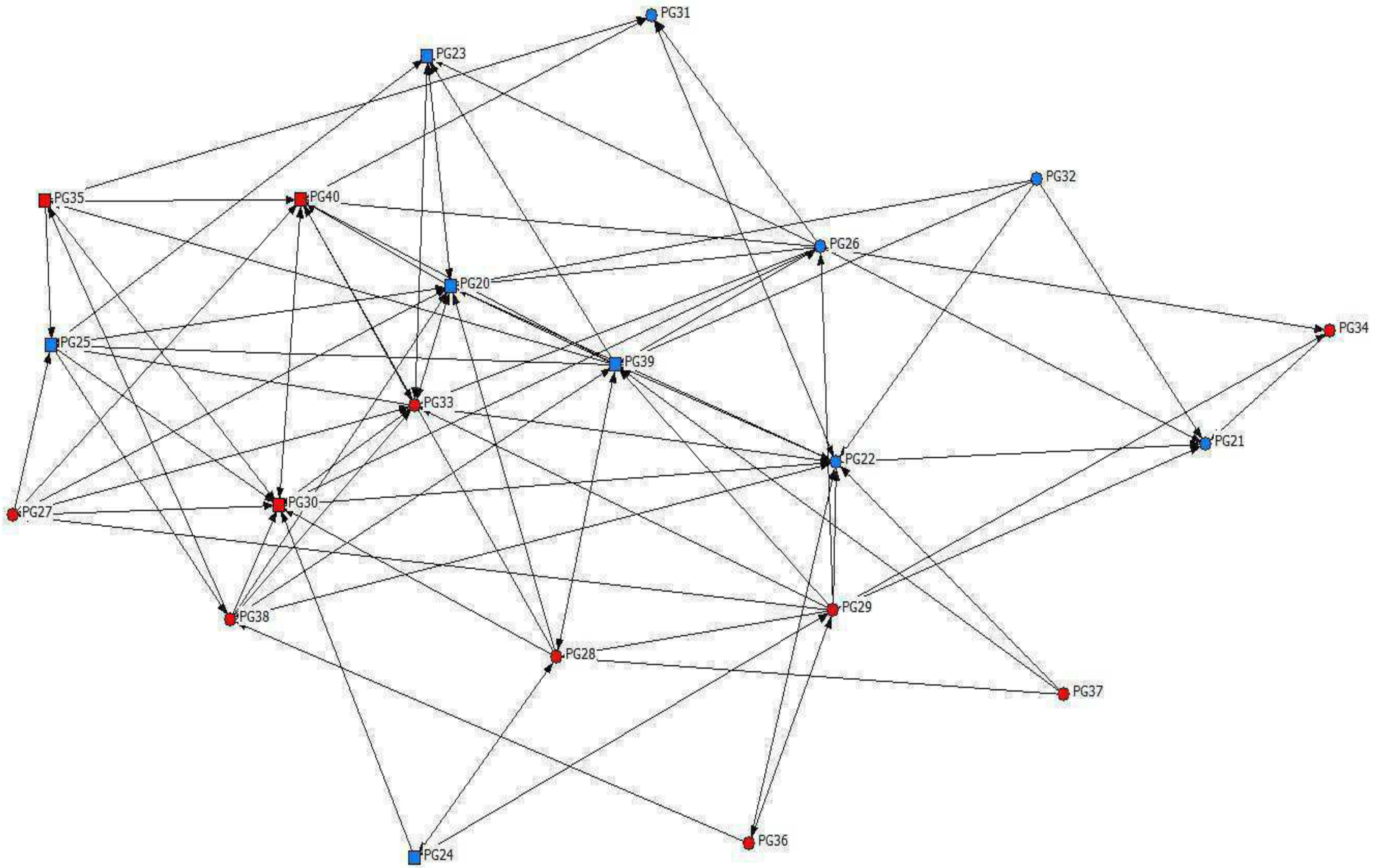
Figure 3 depicts a greater density among the actors compared to Semesters 1 and 2. More key players had emerged, although the class representatives were still occupying an important position in the network.

Figure 2: Sociogram of the network in Semester 2



Source: Estimated from data

Figure 3: Sociogram of the network in Semester 3



Source: Estimated from data

3.4 Position of different actors

The analysis of centrality, hub and authority scores indicate the position of the actors (Appendix Tables A1 and A2). In the first semester, the class representatives (PG22 and PG39) were central actors, with high centrality, hub and authority scores. The authority score of PG22 was much higher than the hub score while it was the opposite in the case of PG39. In other words, while PG22 could provide information directly, PG39, on the other hand, could collect the information successfully and pass it on to other students. With the progression of the semesters, however, their importance in the network declined. It may be attributed to their poor academic performance. The class representatives were displaced by other students as key actors in the network. For instance, PG20 improved his centrality scores consistently over the semesters. The actor was chosen to be the placement coordinator of the batch at the end of the first semester and was also academically strong (among the top three students). PG20, PG30 and PG33 became authorities while PG20, PG34, PG38, and a few others became hubs by semester 3.

A plausible explanation of the changes is that the actors obtain more information about each other as they interact with each other. Starting from the second semester, they also obtain information about academic merit as grades are published. Students who performed better became more prominent. However, there was a non-linearity as students who performed best was not willing to share information with other students. For instance, PG31, who was the topper of the batch, did not interact with his peers. Actors, therefore, established connections with their peers who were close to the top *and* shared information. In the second and third semesters, placement and internship emerged as important issues. As a result, the importance of placement coordinators (PG20 and PG40) rose in these semesters as they provided information about the prospective companies and internship opportunities to their peers.

Thus, the pattern of tie-formation changed over time as actors obtained the information necessary to identify high value actors. The influence of academic performance and other academic accomplishments of actors appear to become increasingly important in determining their position in the network. This is indicated by the analysis of the sociograms and ego-centric measures implying that H3 (increase in the number of high value actors) should hold. However, the network did not resemble the star formation. Rather, there are inter-connections between actors.

3.5 Stability and efficiency of network

Changes in the fragmentation scores (reported in Table 2; 0.22 in Semester 1, 0.10 subsequently) and the stability and expansion ratios (see Table 4) indicates that the network has become more stable over time. Since forming and maintaining ties was costly—once information was received about the helpfulness, academic strength and the nature of the different actors—the actors discarded old ties that yielded less benefit and developed bonds with relatively more high valued actors.

Table 4: Changes in ties over semesters

	Semester 1 & 2		Semester 2 & 3	
Ego	**Stability Ratio**	**Expansion ratio**	**Stability Ratio**	**Expansion ratio**
PG20	0.500	2.000	0.600	0.200
PG21	1.000	0.000	1.000	0.000
PG22	0.889	0.222	0.600	0.000
PG23	0.500	1.500	0.500	0.250

Ego	Semester 1 & 2		Semester 2 & 3	
	Stability Ratio	Expansion ratio	Stability Ratio	Expansion ratio
PG24	1.000	0.250	0.600	0.000
PG25	0.500	0.000	0.333	1.000
PG26	0.500	1.000	1.000	0.500
PG27	0.000	2.000	0.750	0.500
PG28	0.000	0.000	0.750	0.500
PG29	1.000	1.667	1.000	0.250
PG30	1.000	0.250	0.600	0.000
PG31	0.500	0.000	1.000	1.000
PG32	0.167	0.167	0.500	1.500
PG33	0.400	0.200	1.000	0.667
PG34	0.333	0.333	0.000	1.000
PG35	0.500	1.000	0.667	0.667
PG36	0.000	1.000	1.000	0.500
PG37	1.000	0.000	1.000	0.500
PG38	1.000	5.000	0.833	0.167
PG39	0.417	0.167	1.000	0.286
PG40	0.500	0.000	0.000	3.000
Mean	**0.557**	**0.798**	**0.702**	**0.595**

Source: Estimated from data.

If we correlate the change in ties with academic performance in the previous semester, we find that students had tried to establish new ties with peers who had secured high grades, and discarded peers whose performance was below par. Such behaviour was reflected in the significant decline in mean rank of peers between the first two semesters from 10.298 to 8.582 (Table 5); this difference is statistically significance at a 10% level. Subsequently, however, the change was marginal and not statistically significant at all percents. Over time, therefore, the network became more stable and efficient (H4).

Table 5: Mean of ranks of peers in each semester

Statistic	Semester 1	Semester 2	Semester 3
Mean	10.298	8.582	8.847
t-statistic		1.518*	-0.207

*Note: *, ** and *** denotes Prob. < .10, < .05 and < .01, respectively.*
Source: Estimated from data.

4. Discussion and conclusion

To sum up, the results of this study indicate increasing interaction among actors reflected in increases in average degree, density and reachability. Centrality scores (degree and closeness) also rises, though marginally. In the absence of information, actors initially form ties based on an easily observed indicators (undergraduate college) and consider the class representatives as high value actors. With increasing interaction, however, actors obtain greater information about their peers. It leads to the decline in the value of the class representatives, emergence of more high value actors and a shift towards marks-based homophily and polarisation. Consequently, the network became more efficient and stable. Thus, the four hypotheses framed are all validated.

Existing studies have reported that, though networks will become denser, more connected integrated (Barnett 2001), their geodesic distance will increase over time (Spencer 2003). Literature also reports that new entrants to a network cluster together (Bernard 2013); however, the basis of tie formation changes over time (O'Malley and Christakis 2011) and may lead to polarisation (Jackson and Xing 2014; McPherson, Smith-Lovin, and Cook 2001). These is also evidence that increasing interaction generates information and enables identification of high value actors (Roth and Schoumaker 1983; Chen et al. 2014). It increases efficiency of the network (Long, Hibbert, and Braithwaite 2016; Bottinelli, Gherardi, and Barthelemy 2019; Barnett 2001); along with the emergence of multiple high value actors the network, therefore, becomes more stable over time (Dakin and Ryder 2020; Bowker 2004). The present study confirms all these findings.

On the other hand, the findings of this study contradicts that of existing studies reporting increasing dependence on a few key value actors leading to a fragile (Malin and Carley 2007) and less clustered network (Scribani et al. 2021). The results of the present study also differs from that of studies reporting that actors tend to form ties with known peers (Jackson and Rogers 2007; Biggs and Shah 2006; Biggs, Raturi, and Srivastava 2002). Nor does this study observe the creation of star networks reported by Goeree et al. (2009).

This study highlights the importance of obtaining information through greater interaction in a community characterised by actors with varying and unknown levels of productivity. Results reveal that the network will become stable, efficient but polarised over time. This is an important finding which is becoming increasingly recognised in literature (Sih, Hanser, and McHugh 2009). It has implications beyond student communities and applies in contexts like group-based production, evolution of communities with unequal distribution of endowments, etc.

The small sample size is a major limitation of this study. As pointed out Leung (2019), making inferences from the results using statistical tests is possible under very restrictive conditions. So we have not performed any statistical tests of significance to confirm the hypotheses. The present study is, therefore, exploratory and indicates a possibility that needs to be explored through studies using larger samples. However, the small sample size does enable the study of the complete network and all ties.

The present study examines the formation of ties among actors with unequal endowments and lacking information. Analysis reveals that lack of information in the initial stages of interaction need not constrain the movement towards efficiency. Repetitive interaction in a dynamic context may generate information and create stable and efficient ties between actors. This is an encouraging finding. However, the normative implications of these findings needs to be explored. The efficiency of the network is attained with a cost in the form of increasing polarisation among actors. Now, the raison-d'être of networks is the spill over of positive externalities within the community (Kincaid 2000; Fowler and Christakis 2009). The creation of a polarised society imposes barriers to the dissipation of externalities within the community. It calls for the creation of overlapping structures measures like mediation (Bartolomeo and Papa 2016) and exogenous appointment of bridging players (Musiał and Juszczyszyn 2009). A study of the possible conflict between efficiency and equity in heterogeneous networks comprises an important area of research for the future.

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SOFTWARE

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Appendix: Questionnaire

Questionnaire administered after Semester 1 using Google form:

1. Class Roll No:
2. Name:
3. Which of your class mates did you seek help from to obtain information about academic information in Semester 1:

Questionnaire administered after Semester 2 using Google form:

1. Class Roll No:
2. Which of your class mates did you seek help from to obtain information about academic information in Semester 2:

Questionnaire administered after Semester 3 using Google form:

1. Class Roll No:
2. Which of your class mates did you seek help from to obtain information about academic information in Semester 3:

Note:
Information on gender, religion, social group, under graduate college and marks was obtained from University records.

Table A1: Actor-wise centrality scores

Actor	Degree Centrality			Closeness Centrality			Betweenness Centrality		
	Semester 1	Semester 2	Semester 3	Semester 1	Semester 2	Semester 3	Semester 1	Semester 2	Semester 3
PG20	0.20	0.50	0.55	0.56	0.67	0.69	0.00	0.06	0.06
PG21	0.10	0.15	0.25	0.53	0.53	0.54	0.00	0.00	0.02
PG22	0.85	0.70	0.55	0.87	0.77	0.69	0.3	0.26	0.12
PG23	0.25	0.35	0.25	0.57	0.57	0.54	0.00	0.01	0.00
PG24	0.25	0.25	0.15	0.57	0.57	0.5	0.01	0.01	0.00
PG25	0.30	0.25	0.40	0.59	0.56	0.59	0.01	0.01	0.02
PG26	0.25	0.50	0.50	0.57	0.65	0.67	0.01	0.1	0.09
PG27	0.15	0.20	0.30	0.54	0.51	0.57	0.00	0.0	0.01
PG28	0.35	0.35	0.35	0.61	0.59	0.61	0.04	0.04	0.04
PG29	0.25	0.40	0.50	0.57	0.63	0.67	0.01	0.08	0.12
PG30	0.25	0.40	0.50	0.57	0.63	0.67	0.01	0.05	0.07
PG31	0.25	0.20	0.20	0.57	0.50	0.54	0.00	0.00	0.01
PG32	0.30	0.10	0.20	0.59	0.49	0.54	0.01	0.00	0.00
PG33	0.45	0.40	0.50	0.65	0.59	0.67	0.03	0.03	0.04
PG34	0.20	0.20	0.15	0.56	0.51	0.49	0.00	0.01	0.00
PG35	0.10	0.20	0.30	0.53	0.5	0.56	0.00	0.00	0.01
PG36	0.15	0.10	0.15	0.54	0.44	0.51	0.00	0.00	0.00
PG37	0.10	0.10	0.15	0.51	0.47	0.51	0.00	0.00	0.00
PG38	0.10	0.35	0.40	0.53	0.59	0.61	0.00	0.06	0.03
PG39	0.90	0.50	0.60	0.91	0.67	0.71	0.36	0.06	0.11
PG40	0.15	0.50	0.45	0.53	0.65	0.63	0.00	0.09	0.04

Source: Estimated from data

Table A2: Hubs and Authority Scores

Actor	Hub			Authority		
	Semester 1	Semester 2	Semester 3	Semester 1	Semester 2	Semester 3
PG20	0.111	0.242	0.190	0.217	0.397	0.438
PG21	0.101	0.053	0.041	0.144	0.175	0.199
PG22	0.350	0.487	0.304	0.577	0.298	0.249
PG23	0.104	0.311	0.168	0.258	0.215	0.223
PG24	0.214	0.166	0.089	0.092	0.076	0.084
PG25	0.313	0.188	0.187	0.070	0.192	0.230
PG26	0.274	0.287	0.416	0.120	0.119	0.101
PG27	0.167	0.218	0.290	0.040	0.038	0.043
PG28	0.052	0.215	0.256	0.298	0.129	0.126
PG29	0.158	0.216	0.264	0.201	0.074	0.024
PG30	0.203	0.214	0.157	0.230	0.315	0.398
PG31	0.167	0.053	0.098	0.189	0.217	0.172
PG32	0.326	0.074	0.193	0.000	0.000	0.000
PG33	0.226	0.164	0.267	0.318	0.348	0.365
PG34	0.190	0.141	0.049	0.083	0.089	0.111
PG35	0.167	0.187	0.188	0.000	0.105	0.099
PG36	0.167	0.040	0.059	0.028	0.038	0.043
PG37	0.153	0.076	0.110	0.000	0.000	0.000
PG38	0.052	0.272	0.301	0.083	0.150	0.091
PG39	0.473	0.319	0.311	0.375	0.294	0.300
PG40	0.053	0.034	0.152	0.173	0.446	0.353

Source: Estimated from data