Evolution and Formation of Indian Parliamentary Debate Networks

Satyam Mukherjee

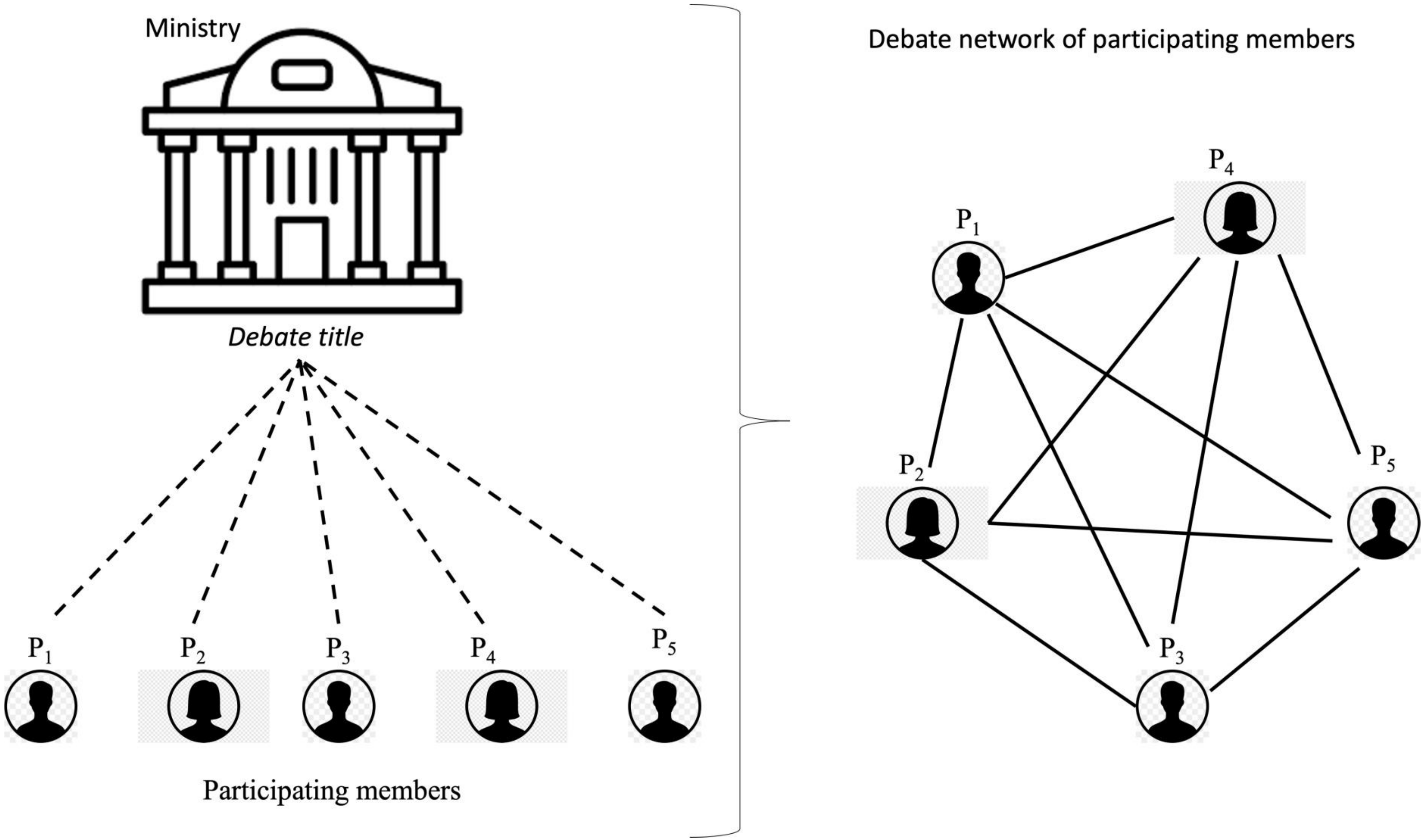
School of Management & Entrepreneurship, Shiv Nadar Institution of Eminence

satyam.mukherjee@snu.edu.in

Rajya Sabha Debates

- Data source: https://rsdebate.nic.in/
- The Indian legislature is an interesting case to study, given that its parliamentary system of governance contrasts with the presidential system in the US, Argentina, and Chile.
- The Rajya Sabha (or the Upper House of the Indian Parliament) has been drafting rules, procedures, regulations, conventions, and precedents.
- The “Question Hour” in the Rajya Sabha exemplifies a setting where a network of debating members naturally emerges.

Construction of the Debate Network



Debate Network: Example

- Two members participated in the debate on the *Divisional Office for Railways* on May 27, 1952: Baidyanath Rath and Radhakrishna Biswasroy.

- In another example, consider the *Raw Silk Industry* debate on May 27, 1952, involving the following members: Mohamed Valiulla, M. Govinda Reddy, H. D. Rajah, K. C. George, and Jaspat Roy Kapoor.

- In this case, a debate network of participating members of 5 nodes is generated with 10 edges – (Mohamed Valiulla – M. Govinda Reddy), (Mohamed Valiulla – H. D. Rajah), (Mohamed Valiulla – K. C. George), (Mohamed Valiulla – Jaspat Roy Kapoor), (M. Govinda Reddy – H. D. Rajah), (M. Govinda Reddy – K. C. George), (M. Govinda Reddy – Jaspat Roy Kapoor), (H. D. Rajah – K. C. George), (H. D. Rajah – Jaspat Roy Kapoor), and (K. C. George – Jaspat Roy Kapoor).

- Weighted and undirected networks of Rajya Sabha members.

Node-level attributes

- Our analysis extracts the following variables for the Rajya Sabha members: the *k*-core index, Burt's constraint (Burt, 1997, 2004), and the member's local clustering coefficient (LCC).

- We infer the gender of each Rajya Sabha member from their prefixes in our data.

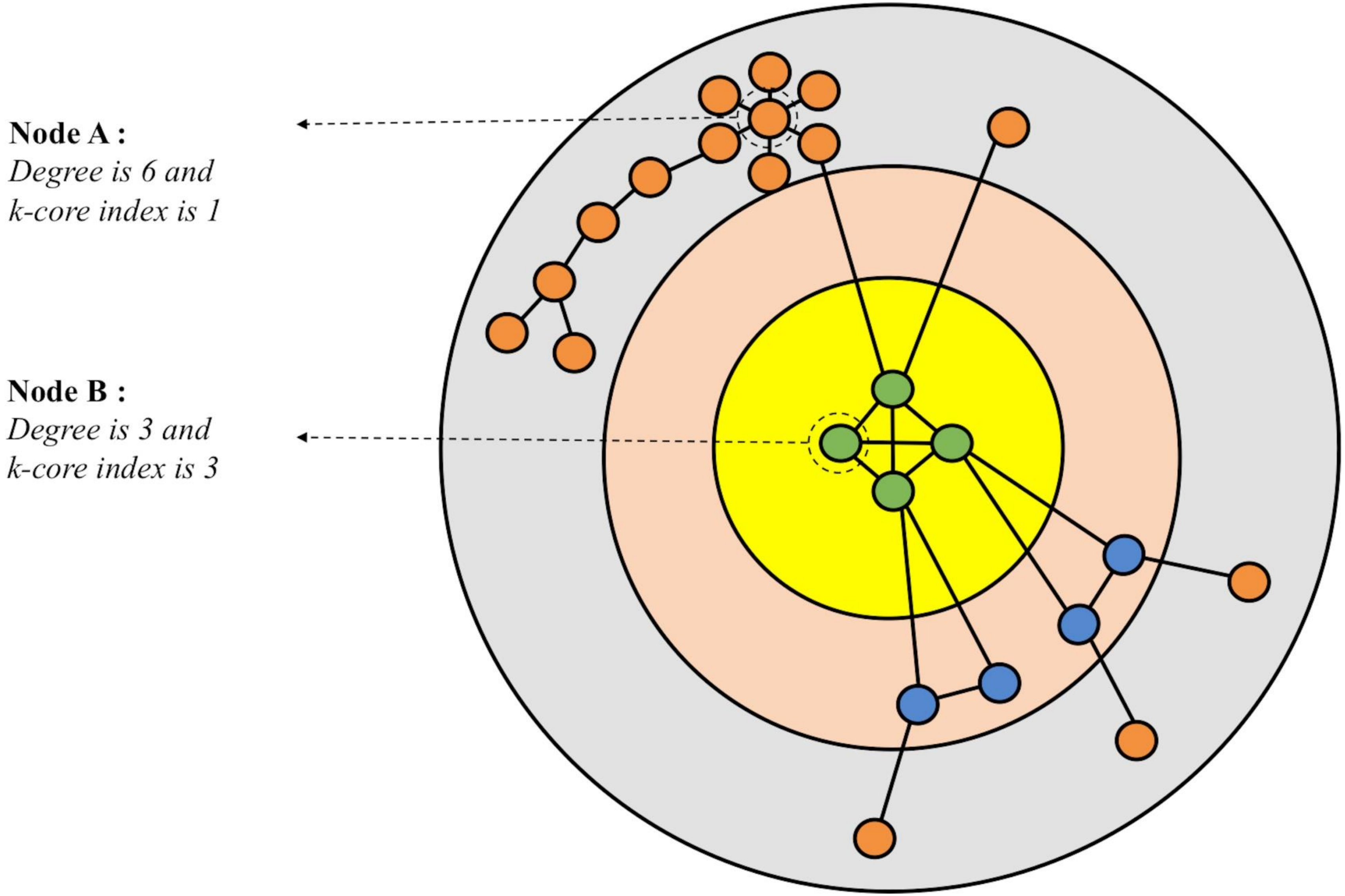
- Members with the prefix "*Shri*" are identified as male.

- Female parliamentarians are identified with the prefix "*Shrimati*", and "*Kumari*".

- We manually extracted the educational qualifications of the parliamentarians from the Rajya Sabha biographical handbook.

- 11 categories for the highest educational degree: Doctorate, Undergraduate, Graduate, Professional Graduate, Post Graduate, Professional Post Graduate, Intermediate, Matriculation, Under Matric, Diploma, and No-Formal Degree.

k-core decomposition



Structural Holes and Burt's constraint

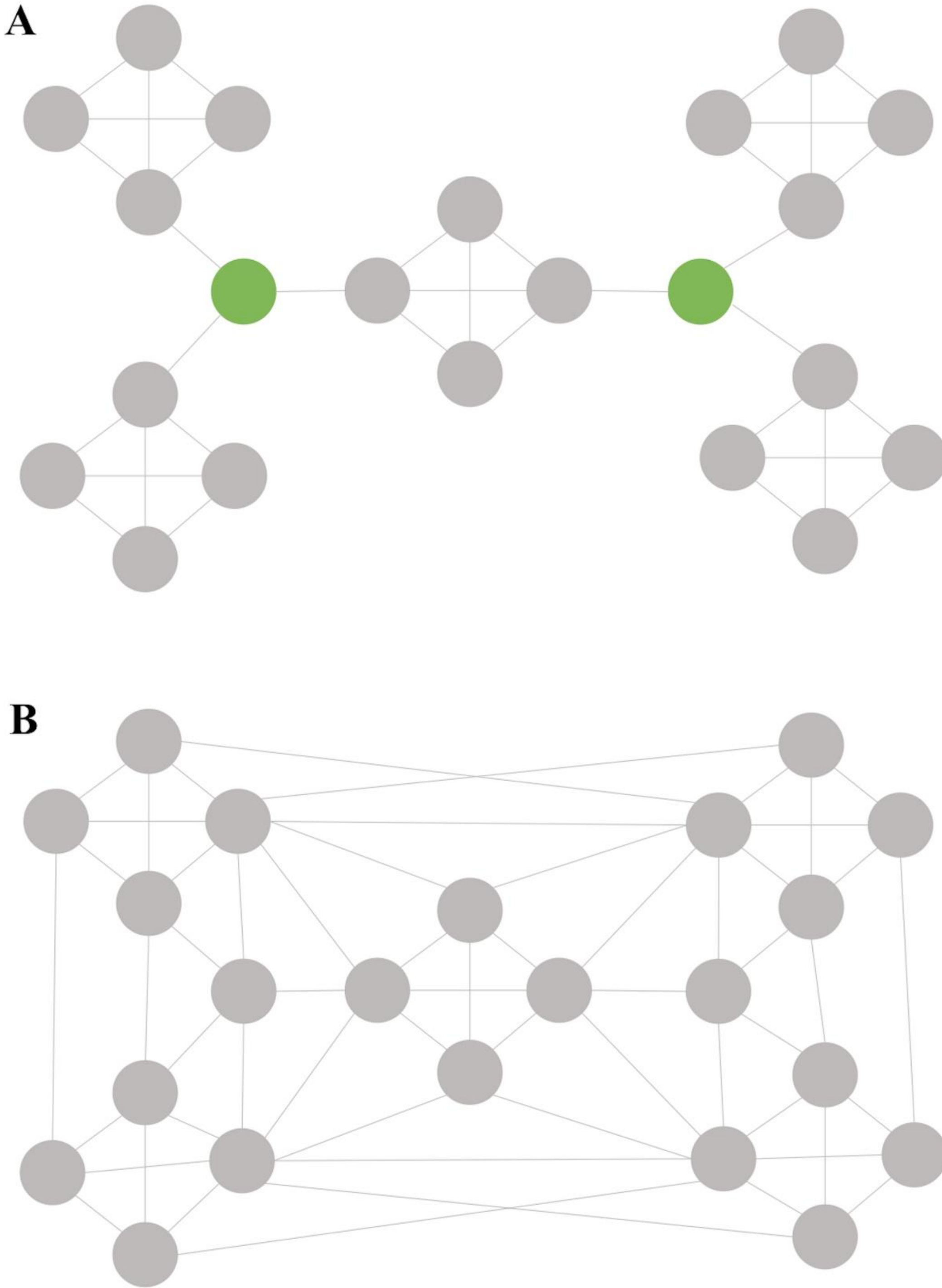
- User nodes marked by a green colour act like a bridge to connect various user groups (which otherwise would be disconnected).
- The number of structural holes is higher in Figure A than in the network in Figure B.
- Due to a lower number of structural holes, network cohesiveness is high in Figure B.

$$C_{it} = \sum_j c_{ijt}; i \neq j,$$

where C_{it} is the network constraint of a debater i. In the above expression, c_{ijt} is the measure of i's dependence on neighbor j, given by:

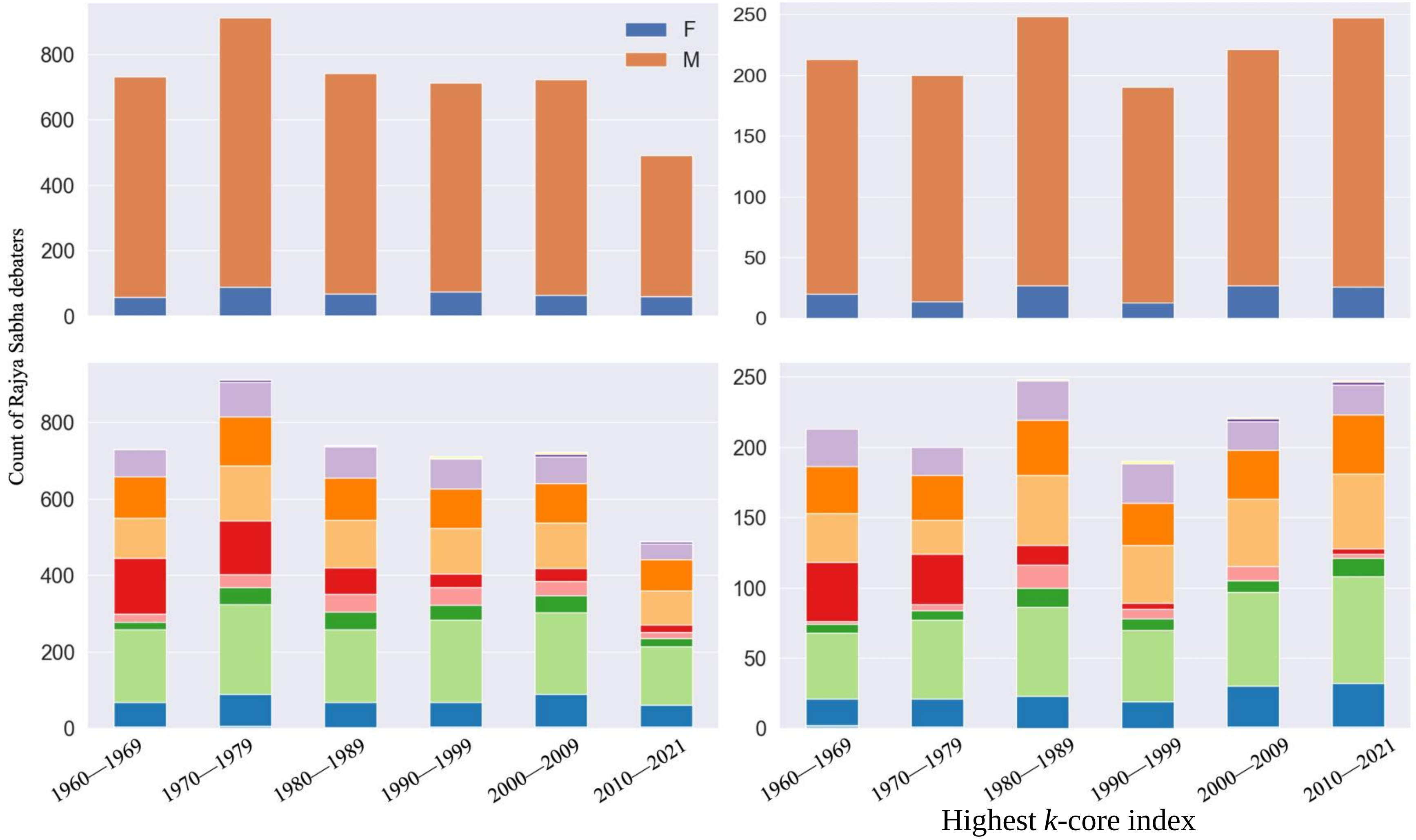
$$c_{ijt} = \left[S_{ijt} + \sum_q \left(S_{iqt}S_{qjt}\right)\right]^2 ; i \neq j \neq q,$$

where S_{ijt} is the proportional measure of links between debater i on the direct contact j during the time period t, while $S_{iqt}S_{qjt}$ estimates the product of the proportion of indirect ties between debater i to debater q, and debater q to debater j during the time period t. This measures the extent to which a parliamentarian's external alters (direct contacts and indirect contacts) share relationships with each other. Higher values of this constraint for a debater imply that its external alters are more connected, thereby indicating fewer structural holes.

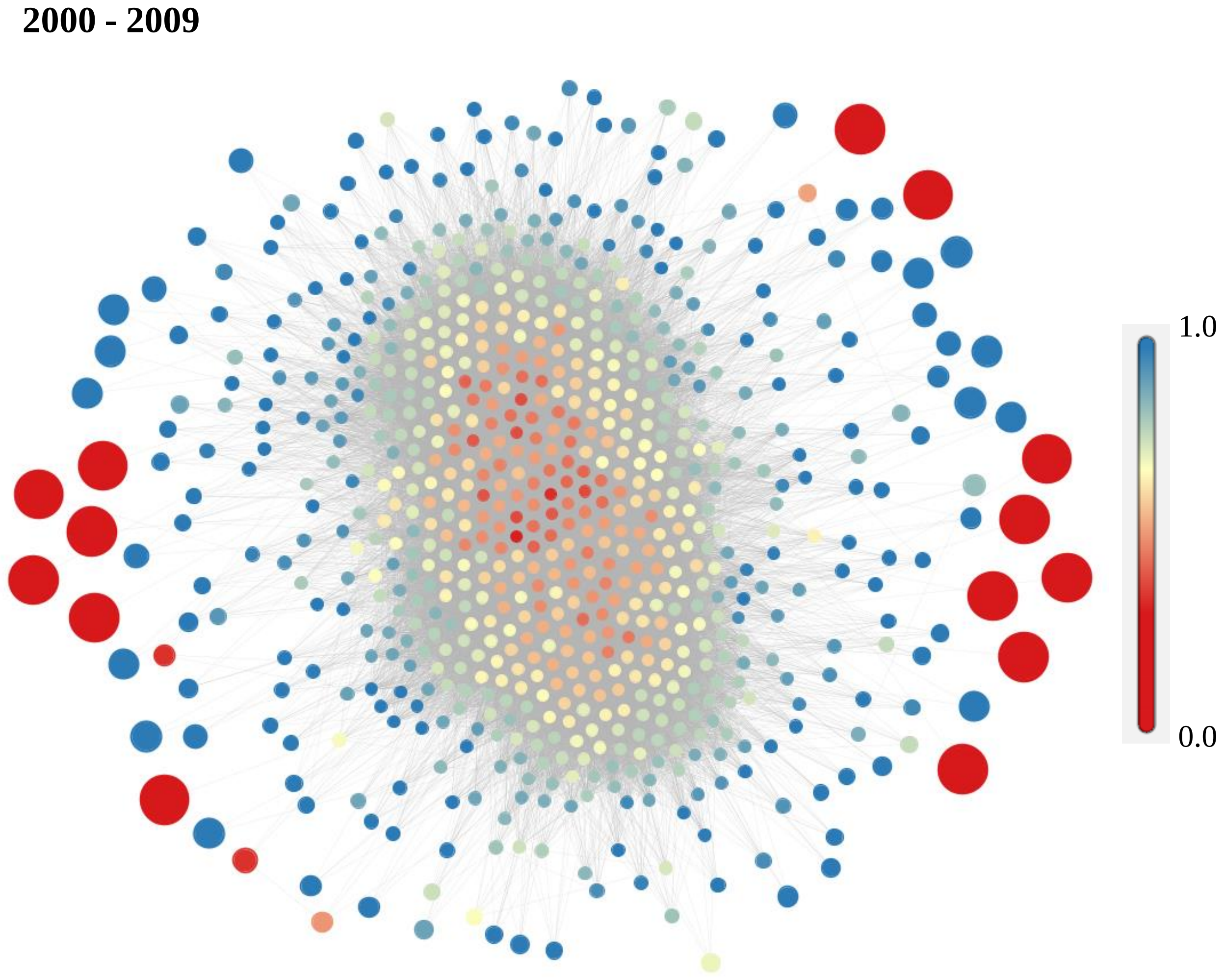


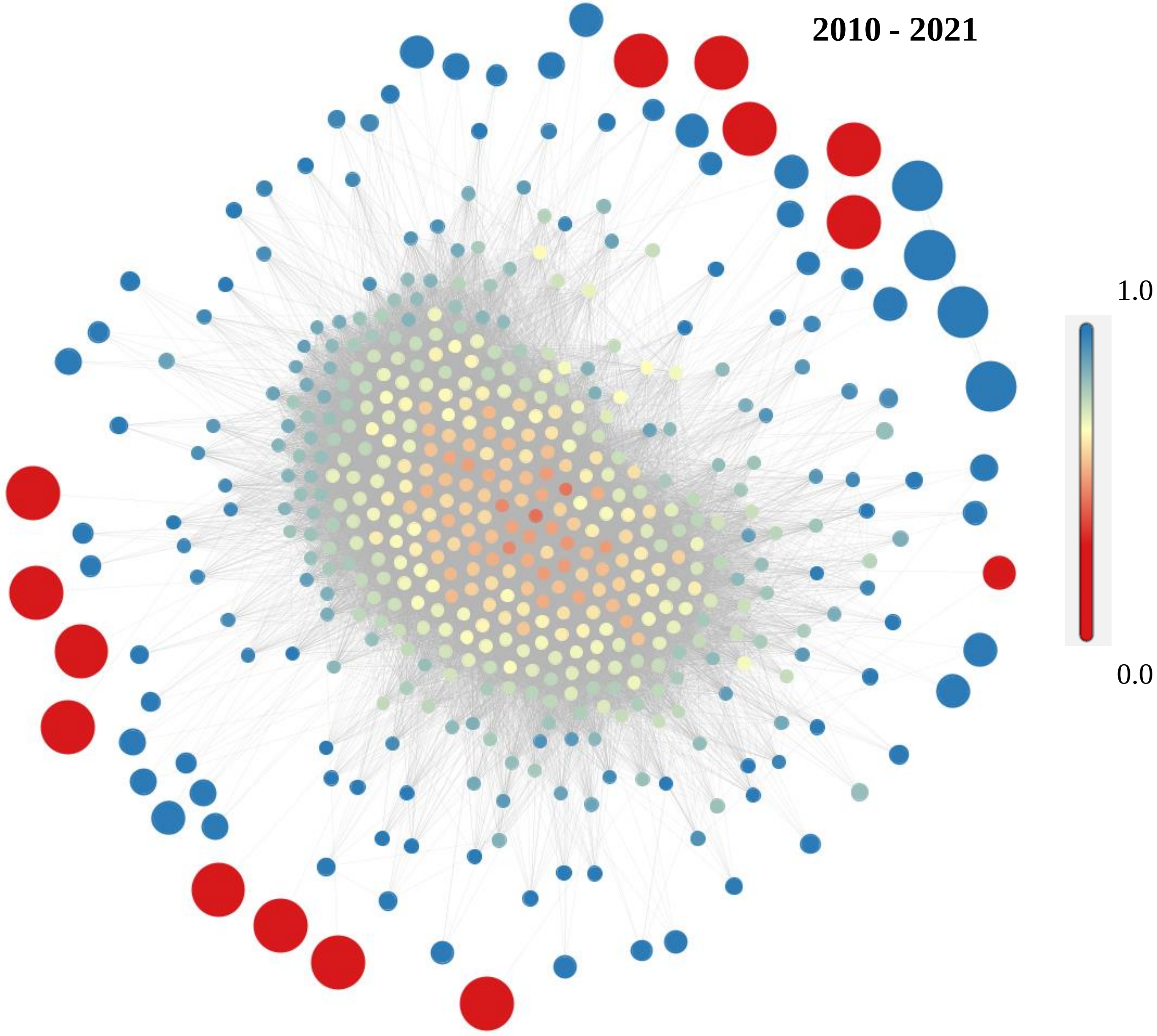
Exploratory Analysis

Gender and Education



Undirected and weighted Networks





Colour: LCC; *Size*: Burt’s constraint

Research Questions

We empirically examine the significance of node-level determinants and the role of homophily in predicting tie formation among Rajya Sabha members.

valued-Exponential Random Graph Model (valued-ERGM)

We use valued Exponential Random Graph Models (ERGM) to estimate, in addition to the dyadic differences between parliamentarians, the impacts of the structural tendencies of the network of debating parliamentarians. A basic valued ERGM of a set of n parliamentarians as:

$$\Pr(Y = y) = \left(\frac{1}{\kappa}\right) h(y) \exp\left(\sum_k \theta_k Z_k(y, x)\right)$$

Where Y is an array of size $n \times n$ containing the count of ties of network variables with y realizations, X is an array of size $n \times p$ containing individual attributes with x realizations, $Z_k(y, x)$ is a network statistic corresponding to any realization of y, θ_k is the coefficient of network statistics $Z_k(y, x)$, and $\frac{1}{\kappa}$ is a normalizing constant to ensure the feasibility of a range of probability values between 0 and 1. The summation is taken over all the network statistics, which are included in the model.

valued-Exponential Random Graph Model (valued-ERGM)

Finally, $h(y)$ refers to the *reference distribution*, which addresses the question of the distribution of counts of ties in the absence of any model terms. Since there is no upper bound to the values of weights between two parliamentarians, a *Poisson* distribution becomes a natural choice for the reference distribution. However, the over-dispersion in the weights leads us to choose the *Conway-Maxwell-Poisson* (COM-Poisson) distribution as the reference distribution in our analysis.

Valued-ERGM Estimates

Estimates from the valued-ERGM; †$p<0.10$, *$p<0.05$, **$p<0.01$, ***$p<0.001$

Model fit: Bayesian Information Criterion (BIC): $BIC = -2\ln(L) + k\ln(N)$

1950 - 1959				
	Model 1	**Model 2**	**Model 3**	**Model 4**
Nonzero	-3.617*** (0.017)	-3.414*** (0.017)	-3.550*** (0.022)	-3.500*** (0.019)
Sum	1.865*** (0.047)	1.387*** (0.043)	1.607*** (0.070)	1.867*** (0.050)
***k*-core index**	0.0007*** (0.0001)	0.0012*** (0.0001)	0.001*** (0.0003)	0.001*** (0.0001)
Burt's constraint	-0.492*** (0.031)	-0.422*** (0.025)	-0.424*** (0.041)	-0.384*** (0.026)
LCC	-0.727*** (0.018)	-0.557*** (0.014)	-0.603*** (0.024)	-0.689*** (0.017)
Nodefactor (Gender: Male)		0.057** (0.020)		-0.083*** (0.016)
Nodematch(Gender)		-0.053* (0.028)		0.085*** (0.018)
Nodefactor (Highest Degree)				
Graduate			-0.021 (0.011)	-0.034*** (0.008)
Professional Graduate			0.023 (0.013)	0.014 (0.010)
Post Graduate			-0.031** (0.011)	-0.052*** (0.010)
Professional Post Graduate			0.028* (0.011)	0.039*** (0.009)
Doctorate			-0.146*** (0.016)	-0.168*** (0.011)
Intermediate			0.078*** (0.015)	-0.021 (0.013)
Matriculation			0.155*** (0.020)	0.131*** (0.013)
NoFormalDegree			-0.053*** (0.012)	-0.082*** (0.008)
Nodematch (Highest Degree)			-0.001 (0.008)	0.0002 (0.006)
Bayesian Information Criterion (BIC)	-331920	-340434	-365076	-359353

1960 - 1969				
	Model 1	**Model 2**	**Model 3**	**Model 4**
Nonzero	-4.058*** (0.022)	-3.823*** (0.015)	-3.826*** (0.014)	-4.013*** (0.021)
Sum	0.814*** (0.042)	0.913*** (0.035)	0.649*** (0.040)	1.234*** (0.056)
***k*-core index**	0.0007*** (0.00009)	0.0009*** (0.00007)	0.0011*** (0.00009)	0.0006*** (0.0001)
Burt's constraint	-0.193*** (0.027)	-0.170*** (0.022)	-0.058* (0.024)	-0.173*** (0.034)
LCC	-0.051** (0.019)	-0.095*** (0.014)	-0.040* (0.017)	-0.081*** (0.021)
Nodefactor (Gender: Male)		-0.082*** (0.009)		-0.243*** (0.013)
Nodematch(Gender)		-0.002 (0.009)		0.096*** (0.014)
Nodefactor (Highest Degree)				
Graduate			-0.002 (0.009)	0.003 (0.013)
Professional Graduate			0.039*** (0.009)	0.064*** (0.010)
Post Graduate			-0.052*** (0.011)	-0.048*** (0.014)
Professional Post Graduate			0.007 (0.010)	0.036* (0.014)
Doctorate			-0.017 (0.012)	0.002 (0.014)
Intermediate			-0.103*** (0.013)	-0.135*** (0.023)
Matriculation			0.175*** (0.012)	0.168*** (0.022)
NoFormalDegree			-0.054*** (0.009)	-0.045*** (0.013)
Nodematch (Highest Degree)			-0.018+ (0.011)	0.004 (0.013)
Bayesian Information Criterion (BIC)	-736212	-693698	-673061	-670720

2010 - 2021				
	Model 1	**Model 2**	**Model 3**	**Model 4**
Nonzero	-3.712*** (0.018)	-3.694*** (0.016)	-3.658*** (0.019)	-3.581*** (0.019)
Sum	0.815*** (0.037)	1.043*** (0.037)	0.870*** (0.035)	0.883*** (0.049)
***k*-core index**	0.003*** (0.00008)	0.002*** (0.00006)	0.003*** (0.0008)	0.003*** (0.0008)
Burt's constraint	0.123*** (0.018)	0.105*** (0.014)	0.110*** (0.017)	0.114*** (0.019)
LCC	-0.247*** (0.013)	-0.298*** (0.014)	-0.267*** (0.013)	-0.253*** (0.016)
Nodefactor (Gender: Male)		-0.045*** (0.018)		-0.083*** (0.011)
Nodematch(Gender)		0.007 (0.012)		0.025 † (0.014)
Nodefactor (Highest Degree)				
Graduate			-0.009 (0.011)	0.019 (0.013)
Professional Graduate			0.083*** (0.011)	0.107*** (0.013)
Post Graduate			0.027* (0.011)	0.035** (0.013)
Professional Post Graduate			-0.053*** (0.013)	-0.018 (0.015)
Doctorate			-0.023* (0.011)	0.002 (0.013)
Intermediate			0.073*** (0.012)	0.026 † (0.014)
Matriculation			-0.207*** (0.019)	-0.256 *** (0.017)
NoFormalDegree			-0.029* (0.014)	0.002 (0.016)
Nodematch (Highest Degree)			-0.017** (0.005)	0.0005 (0.006)
Bayesian Information Criterion (BIC)	-361154	-357483	-361392	-346853

Discussions

The longitudinal data of the networks provides us with mixed insights.

Visual inspection provides insight into the highly clustered groups of individuals connected to members who rarely participated in any debate

A higher number of structural holes through the decades reveals how the upper House of the Indian Parliament functions – members are not constrained by with whom they debate; rather, they keep debating outside a cohesive pool of parliamentarians.

The density decreased over time and increased in the recent decade, suggesting the exit of veterans and the entry of new politicians in the Rajya Sabha.

Even though the representation of women in the Rajya Sabha is quite low, post-1970s, their presence in the core of the debate networks is significantly high.

The estimates from the valued-ERGM confirm that education and gender matter in tie formation, but the intensity of education homophily and gender homophily keeps changing through the decades.

Conclusions & Future Research

Education homophily has higher statistical power than gender homophily in the upper house of the bicameral parliament of India.

Even though education homophily dominates gender homophily and other exogenous factors, the effect was positive in the 1980s and became negative in the ensuing decades.

The significance of the homophily terms in terms of educational qualifications and gender participation has policy implications for Government bodies that emphasise gender diversity in decision-making.

A recent study on educated leaders in India observed that even though educated leaders impact the educational outcomes of their constituencies, there is no effect on less developed states (Lahoti & Sahoo, 2020).

Prospect of implementing NLP-based tools to study the topics of the debate text and analyze the semantic diversity of the parliamentarians

Further, while we have focused primarily on the role of education and gender, we cannot account for the heterogeneity in the economic status of the parliamentarians. Quantifying such heterogeneities is thus the subject of potential research opportunities.

Questions