Caste Capital on Twitter: A Formal Network Analysis of Caste Relations among Indian Politicians

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Twitter is increasingly important for political outreach and networking around the world. While electoral politics and social relations in India are heavily organized by caste, a broader rhetoric of castelessness among upper-caste politicians has led to the eschewing of caste publicly to appear secular. This has rendered caste dynamics more implicit than explicit. Social media, often cited as a tool for inclusion, offers a unique window into the networks of covert exclusion. Our study analyzes three structural properties of the Twitter network of Members of Parliament in India - influence, bridging capital, and mutual connectivity, to understand how caste manifests as social capital in the information economy. Our results show that those higher in the caste hierarchy are structurally poised for higher social capital through higher influence, incoming bridging capital, and higher propensity for mutual connections with other MPs in the network. Our study offers a methodological window into these invisible relations to show how structural advantages of Brahmanical supremacy are being co-produced and stabilized on social media at the highest level of politics.

CCS Concepts: • **Human-centered computing** → **Empirical studies in collaborative and social computing**; **Social network analysis**.

Additional Key Words and Phrases: Caste, Social Networks, Social Capital, Twitter, India, Politics

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1 INTRODUCTION

Twitter is a critical platform for public and political discourse in India. While the number of users remain less than 20 million in 2021, the country has its fastest growing user base [22]. Traditional political mobilization uses various forms of caste-based outreach, but there has been a significant shift in political communication among party elites who no longer engage significantly with mainstream press. Twitter is one of the primary platforms for outreach among the country's political class since the 2014 General Elections [4, 50]. Consequently, important elements of political branding and engagement are enacted on Twitter, making it a crucial site for scholarly examination. The importance of caste relations and politics cannot be overstated for electoral politics as it deeply

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influences social, cultural or economic relations in contemporary India. Caste is also a central component of voting behavior and caste-based mobilization is a key element of articulation of democratic rights among the country's marginalized populations[95].

A nascent area of work with few methodological interventions, one of the key questions facing those interested in the relationship between caste and social computing is that of method: How does one study caste and its evolution within sociotechnical systems? Caste relations can be covert and understood in implicit action, thus the method to study them is not straightforward. The rhetoric of castelessness among upper-caste Indians [29] has also meant that upper-caste politicians tend to eschew caste publicly in the interest of appearing secular in their position. This renders caste relations or dynamics more implicit than explicit. While politicians might not always make explicitly casteist statements or articulation on public fora like Twitter, a deeper examination into the implicit behavior of politicians on social media is necessary to understand how caste operates among them.

Implicit forms of caste discrimination are well understood among lower caste communities who face various forms of an embargo as a result of gate-keeping of valuable social capital within caste networks [74, 113]. While many economists and anthropologists of South Asia have insisted upon studying caste as a network of social relations among individuals [53, 68], there are few empirical and formal studies of caste networks and the kind of social capital it enables in the world of social computing. The role of networks is critical in positions of power. The discreet nature of the interactions between actors, and the assumption of caste identities as static, has led to them being understudied in socio-technical research.

We dispel the myth of castelessness in social computing and show the constructed nature of caste capital as a dynamic entity on social media, particularly in the context of electoral politics. We undertake a study of structural analysis of the Twitter network of Members of the Indian Parliament and its relationship with caste. Lok Sabha, the lower house of the bicameral Indian parliament represents a diversity of representatives elected by direct adult franchise. Our study is comprised of three lines of inquiry:

- First, we use *PageRank* centrality to analyze how prominently MPs of different castes are embedded in the Lok Sabha network. This property allows us to explain the relationship of caste with information consumption and broadcasting. We further examine how occupying influential positions translates into successful information propagation for MPs.
- Second, we examine the relationship between caste of MPs and their bridging capital in the network by measuring *betweenness*, *in-degree*, and *out-degree* centralities. These properties highlight an MP's control over the flow of the information within the directed network and the kind of connections that build their bridging capital -incoming or outgoing.
- Third, we measure the *reciprocity* of individual MPs to examine their likelihood of forming mutual connections with other MPs. Determining the effect of caste on reciprocal following helps us understand who is listening to whom in the network and how reciprocal are relationships between MPs of different castes. Finally, we explore how reciprocity relates to different forms of influence one could exert in the network, measured using PageRank and betweenness.

Our work has implications for the study of Indian politics on social media - we show how caste representation in electoral politics does not translate into social capital within the network of parliamentarians. We find that lower-caste MPs struggle to have access to the kind of influence, bridging capital and mutual connectivity as upper-caste MPs across the ruling and opposition parties. Our work also has implications for the kind of social capital wielded by MPs of different caste groups in ruling vs. opposition parties. This opens up new avenues of understanding the impact of the informational economy on MPs of different castes and their alliance with different parties. Most importantly, our work makes a methodological intervention in the study of social computing and inequality by proposing the study of social networks as a way to study caste relations in sociotechnical systems. Our work is one of the initial attempts at studying caste capital in socio-technical systems, and thus is limited by the data available on the caste of Indian politicians as well as the nature of social media management of their Twitter accounts. We discuss these limitations and possible areas of future work at the end.

2 BACKGROUND AND RELATED WORK

2.1 The Caste System and Electoral Politics in India

Caste is a marker of labor and purity in the ritual hierarchy of Hindu society which also exists in other religions with ethnic roots in the South Asian region [3, 110]. It is legally codified as a protected category in Article 15 of the constitution of India. Affirmative action policies ensure political representation of those lowest in the caste hierarchy - Scheduled Tribes (ST) and Scheduled Castes (SC). Caste and religion are central in Indian politics and at every electoral level.[54]. Sub-caste or *jati* kinship networks continue to be central to social identity, political behavior, and cultural nationalism [10], and inter-regional caste connections impact political alignment [66]. Caste reservations mandate that 24.0% of seats in parliament are reserved for members of Scheduled Castes and Scheduled Tribes communities, and historically, these seats have either been dominated by secular-centrist parties like the Indian National Congress (INC) or parties whose platform is specifically driven by issues of caste.

The rise of the right-wing nationalist Bharatiya Janata Party (BJP) is important in the caste equations of political parties since it is an offshoot of the Rashtriya Swayamsewak Sangh (RSS), historically an upper-caste Hindu paramilitary organization [47]. Moving away from its traditional upper-caste Hindu base in recent elections, BJP has presented itself as a pan-Hindu party and significantly increased its vote base in *Scheduled Castes* and *Other Backward Castes* populations [115]. They have incorporated marginalized caste leaders at the regional and local levels and created strategic alliances with Dalit parties like Lok Janshakti Party [25, 79]. This has caused some shift in who dominates the seats reserved for SCs and STs in the parliament. BJP has effectively represented the lowest jatis (sub-castes) within governance bodies while simultaneously being represented by dominant castes at its national upper echelons[119]. Specifically, the leader of the BJP at the national level, Prime Minister Narendra Modi, belongs to the *Other Backward Castes* category, and the President of India (a nominal post) is a member of the Scheduled Castes [51]. This trend has not necessarily led to mainstreaming lower-caste politicians in the General Elections. Lower-caste candidates are not playing a more central role in electoral politics, but are given tickets to fight elections almost exclusively when constituencies are reserved for lower-caste candidates[73]. upper-caste candidates dominate the electoral rolls of national parties, particularly in states in the Hindi-speaking belt that define national politics in India. These tokenistic representations of a few lower-caste members bolster the optics of castelessness of upper-caste MPs through the idea that identity politics is an issue of lower castes and not of upper castes.

Politicians, particularly at the national level, tiptoe around caste or follow party lines on how to address it. Claims of caste as a declining notion in politics [29] are accompanied by discourse among metropolitan Indians, particularly a younger, aspirational generation, that constructs the discussion of caste as reactionary [82], despite overwhelming contrary evidence [1]. The nature of affirmative action policies requires that lower castes assert their marginalized status to leverage reparations for historical wrongs. Simultaneously, upper castes are able to convert historically accrued caste capital into other kinds of modern social capital, shedding their caste identity or appearing 'casteless' when it suits them [29]. Despite the claims of castelessness by upper castes and constitutional support for lower-caste communities, there is widespread evidence of continuing discrimination, caste-violence, and systematic exclusion of lower-caste communities [97].

Caste is often referred to as the central fault line of modern India [65] because it is a persistent socio-cultural marker that is not just a means of emic affiliation but a mediator of opportunities and resources in Indian society. Compared to upper-caste communities, lower-caste communities tend to be poorer and less educated, and have limited access to public and private institutions. [112]. Lower-caste communities also experience exclusion and segregation when accessing amenities like drinking water, social and religious spaces [101], and housing [46], which has led to ghettoization in the metropoles [11]. Government bureaucracy, the media, the judiciary, and business are dominated by upper castes while lower castes have a negligible presence in leadership and corporate boards [109, 118]. Recent studies have also shown that the upper castes are twice as likely to have high or moderate exposure to social media compared to *Scheduled Castes* and *Scheduled Tribes* [1].

The existing fixation on deprivation and struggle of lower castes in India skews the objectives and outcomes of studies on caste [29]. We interrogate the notion of castelessness by studying follower and friend networks and zooming into the largely understudied "General Category" which is made up of upper castes and a category of *Shudras* called Other Backward Classes (OBCs). While some castes under OBCs are historically more privileged than SCs and STs, they are still disadvantaged under the graded hierarchy by more privileged forward castes. This helps us map networks of forward and backward castes to understand exclusion by empirically studying historical caste privilege among the upper castes and how it manifests in social networks. We propose an empirical method to explore how caste becomes social media capital. We study the relationships between politicians through social media networks to see how caste is relationally performed online.

2.2 Social Media and Politics

In the last decade, social media has become the primary means of communication for politicians around the world [2]. This phenomenon has been examined from various methodological perspectives including brand management, campaign outreach, and outcome predictions [85]. This includes the study of relationships between political speech and its affective dimensions [107], the role of homophily in the spread of information through networks [72], impression management [55] and the construction of public agendas through Twitter [56]. Social media allows politicians to circumvent scrutiny of professional journalists[78] and draw mainstream media coverage through their social media activity [20]. Narrative building on social media helps increase polarization as voters using social media are found to be more opinionated than those not using it, thus actively shaping participation in online political discourse [1].

While upper-caste Hindu parties have historically dominated social media, religious minorities and loosely organized groups opposing the state have recently carved spaces online [100, 116]. Yet, a party like BJP benefits from institutionalized social media management that began before its 2014 general election victory [96]. The party enjoys a well-oiled social media machinery at the national and state levels that promotes its message and undermines opponents [23]. Central diktats have even been issued on how many followers a politician needed to get a ticket in the 2019 general elections [57]. The party closely manages how messages are retweeted through its networks as well as how individual politicians present themselves online [86]. Studies have also shown that among voters with higher social media exposure, BJP enjoyed a distinct advantage over its opponents[1]. The party also benefits by emulating the communication style of its key leader Narendra Modi, who has a massive advantage over all other leaders in the country thanks to his populist style of political communication [87] and careful image building over several years [93].

In the past, social media management for politicians was done by family members or confidantes who were typically younger, social-media savvy technology users. Now, social media management of politicians' accounts is done at three levels: first, at the level of the party; second, at the level of the politician's direct feed; and third, at the level of the specific follower-base of the politician. At the level of the party, BJP's playbook sets the standard that others aspire to [23]. The party's central page for any major platform has 1-3 site administrators, 4-7 editors who post content, and a larger base of a dozen moderators whose job is to manage and respond to comments. These individuals may operate as independent entities not formally affiliated with the party. While some parties train their existing cadres to work on social media, larger parties have professionalized this work by engaging experts from advertising campaigns and journalism [21]. For the majority of the parties, some coordination of messaging happens top-down. Nonetheless individual politicians have their own agendas and issues and may differ on the level of independence they have from central instruction. An individual candidate for a parliamentary seat may have just one social media manager who covers a range of activities—like taking pictures, writing notes, and timing outreach,—while prominent politicians would have dedicated teams.

A motivator of our work is that the majority of quantitative or mixed methods research has examined how social media is used as opposed to what it represents [56]. While there is work on political homophily between social media actors [49], and on echo chambers among politicians [28], little attention has been paid to networks of power and hierarchy as represented in social media relationships. In this paper, we use networks and their articulation as political artifacts to study these relationships with a focus on caste.

2.3 Caste, Networks and Social Capital

Economic and social mobility in India are driven by caste networks. Studies on labor-markets show discrimination against lower-caste candidates for jobs in urban settings and caste based prejudice between borrowers and lenders in Indian banks[9, 38]. Work on entrepreneurship in Tiruppur, Tamil Nadu found that the *Gounder* community counted for a disproportionate share of entrepreneurs in the region, largely driven by caste and kinship networks. They found that Dalit entrepreneurs were unsuccessful because they were excluded from the economic and cultural circuits of the *Gounders* [121]. Similar dynamics extend to the highest levels of industry where research has found evidence of caste-based and religious homophily in the appointments of CEOs and corporate boards [5, 27].

Furthermore, economists have studied how the role of caste networks shape information exchange, access to opportunity, and resource distribution for entrepreneurship, agriculture, education, politics, and labor markets more broadly.These studies suggest that informal social networks of caste strongly affect every aspect of the Indian political economy [6, 45, 67, 69, 70, 111, 122]. Some studies have used a network analysis approach to understand the impact of affirmative action programs on lower-caste communities. They highlight that caste-based cluster formation in Indian society is challenged through affirmative action policies as they reduce the social distance between lower-caste and upper-caste groups[91]. Yet, access to public-sector jobs remains driven by caste-based connections where lower castes tend to lose out as upper-caste communities have connections with powerful people in decision making positions [44].

Srinivas and Beteille suggest studying social networks as a more effective way to understand abstract relations of caste between groups as networks help map out concrete relations between individuals in their diverse roles [104]. Tracing social networks of individuals in a caste society helps understand interpersonal relations and how they unfold. Studies of actor-networks in socio-technical systems have challenged the over-simplification of social relations into binaries of structure and agency [33, 58, 60, 61, 98]. This work reveals that sociological phenomena are a consequence of networks that are *"processual, built activities, performed by the actants out of which they are composed"*[26]. Other works in CSCW have used network analysis to study workplace collaboration and knowledge networks [127]as well as identity formation and its relation to design systems [92]. Drawing from existing work that uses network theory to study political phenomena[62, 124], we study caste and socio-technical systems for their ability to describe and analyze the structure of relations between entities (both human and non-human) in a rigorous but flexible way.

A critical tension between network theory and the study of social capital is the question of measurement [16, 83]. We rely on Borgatti et. al's work to address this tension as their work explicitly studies social capital in a network through structural measures. Patty and Penn theorize three network concepts for understanding political phenomena and relations - centrality, community and connectivity [83]. We use three sub-concepts emerging from these overarching macro-categories - PageRank centrality, betweenness centrality and reciprocity - to undertake an analysis of caste as social capital.

The relationship between the caste of politicians with structural positions in a network can help reveal the caste dynamics of social media. Politicians take a variety of structural positions in their network, some that are conducive to controlling the flow of information between nodes, and others that make them influential in terms of the origin and direction of information. A study of caste networks and their cumulative effects is thus a way to empirically characterize castelessness in India. For example, comparing the degree to which MPs from a particular caste act as bridges between different MPs in the network could reveal if there are certain *communities of caste* that connect different groups of MPs more than others, thus controlling the flow of information between diverse groups in the network. Similarly, measuring centrality or mutuality of connections helps compare how well MPs of different castes are connected to others, how many of these connections are reciprocal, and quantify their importance in terms of these connections.

3 DATA AND DEFINITIONS

Twitter profiles of politicians were accessed from a database created through a machine learning classification pipeline called *NivaDuck* [80]. We use the *Nivaduck* dataset and partial string matching of names to map current MPs in the list. We manually checked the Twitter description, tweet content, account creation date, and party for each of the MPs. At the end of this process, we found that 489 out of 542 current MPs had a Twitter presence.

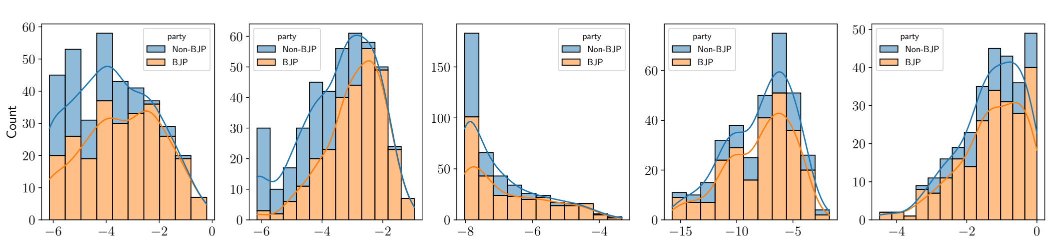


Fig. 1. **Mapping the distribution of network properties for BJP and Non-BJP parties**

Caste categories. To annotate the caste group of each MP, we refer to the SPINPER database [102] that tracks information such as caste, religion, and incumbency of elected MPs of India. We accurately matched the sub-caste or *jati* information of 449 MPs from Hindu religion to one of the six caste categories: (Table 1): *Brahmins*, *Upper-Caste Non-Brahmins* (Non-Brahmins), *Intermediary*

Castes (IC), *Other Backward Castes* (OBC), *Scheduled Castes* (SC), and *Scheduled Tribes* (ST). As discussed before, OBC, SC and ST are considered lower castes as per constitutional mandate. As for the upper castes, we delineate the Brahmins, Non-Brahmin, and Intermediary Castes with the goal of challenging Brahminical supremacy that operates covertly in the guise of castelessness. We believe that categorization and classification is rooted in a kind of ethics that renders something visible and concrete while making other connections or relationships invisible [17]. Our categorization is situated in an anti-caste ethic that looks to sediment caste categories through a process of drawing boundaries. It is inspired from the work of Dalit, Bahujan and Adivasi (lower-caste) scholars, activists and thinkers of the anti-caste struggle in India that fights for equality for all classes, castes, genders and communities [7, 84]. These six meso-level caste categories make the finer inter-*jati* relationships invisible but enable a meaningful statistical study of caste and online networks to glean insights at the group level.

Category	Notation
Brahmins	UCB
Upper-Caste Non-Brahmins	UCNB
Intermediary Castes	IC
Other Backward Castes	OBC
Scheduled Castes	SC
Scheduled Tribes	ST

Table 1. **Notations for caste categories.**

Intermediary castes are a SPINPER categorization that indicate a group of castes that are historically categorized as upper-caste but are fighting for a change of status to lower caste to access affirmative action policies. For remaining upper-caste categories, we separate Brahmins from Non-Brahmins because Brahmins are at the top of the ritual hierarchy that informs the caste system and they continue to have an outsized influence on Indian politics and society. They make up close to 30% of the MPs within Lok Sabha despite being less than 5% of the total population of India [117]. Thus, we work with the following rendering of graded hierarchy in the six caste categories mentioned above based on the *varna* system discussed in section 2 - *Brahmins* > *Upper-Caste Non-Brahmins* > *Intermediary Castes* > *Other Backward Castes* > *Scheduled Castes* > *Scheduled Tribes*.

***Following* network.** Given their prominent position in Indian politics, Lok Sabha MPs often have staffers who manage their social media and are generally mindful of what kinds of language and signalling they should use about their caste or affiliation to other caste groups [76, 94, 105]. However, Lok Sabha MPs caste relations (i.e. relations with politicians from other castes) can manifest in the form of unconscious bias and thus is more evident from a relatively less conspicuous activity on Twitter like *following* someone. We study the influence of caste on the structural properties of the follow network of MPs so as to capture implicit forms of inclusion and exclusion.

We use Twitter's public API to extract the *following* connections among Lok Sabha MPs that were established before February 2020. Half of all MPs' accounts were created before 2016 and close to 98% of total MPs' accounts were created before March 2019 when the National Elections campaigning began, so we expect that their following connections are stable. The following graphs of the MPs are based on a static snapshot at the end of Feb 2020. For our analyses, we consider all retweets sent out and received within March 2019 and February 2020. This time period includes a range of socio-political events, from National Elections of candidates for the Lok Sabha, Ayodhya land dispute that was BJP's core election issue, scrapping of Jammu & Kashmir's statehood which led to a national protest lasting almost a year, as well as various state elections [12, 106].

Out of 489 MPs with active Twitter accounts, 481 follow at least one MP, 465 either follow or are followed by at least one MP, 308 have at least one mutual following connection, and 16 are not connected to any other MP. We excluded 31 MPs from religions other than Hinduism as we had no information about their castes. The size of our final dataset of Lok Sabha MPs is 434.

Influence of Party. We expect the relations between caste and network properties to be correlated with the political party of the MP because of the interplay between different ideologies and whether an MP is from the ruling party. About 60% of MPs on Twitter belong to the ruling party - BJP. The BJP is thus in a hegemonic position – besides its outright parliamentary majority, it is either the ruling party in most Indian states or the primary opposition party. The next major national party, the INC, has only 14% of BJP's strength in the Lok Sabha, and the remainder of parliamentary seats largely go to regional parties with significant presence in just one or two states. Thus, in the rest of the paper, we refer to both the BJP and Non-BJP as "party" though the latter technically includes many parties. Figure 1 shows the difference between the BJP and other parties in terms of various network structural properties. We observe that there is a clear difference in in-degree and out-degree centrality between BJP and Non-BJP. On average, BJP has a higher degree centrality than all the other parties, indicating their dominance in connections.

Controlling for extraneous effects. For each MP in our analysis, we include the age of their Twitter account (in days), self-declared gender (male and female), the predominant language they tweet in, and their cabinet status as control variables to remove the extraneous effects in studying the effect of caste on different network properties. BJP and Non-BJP MPs have a median account age of 5.5 years and 4.0 years respectively. We used the annotations of the gender of MPs as either male or female from SPINPER database [102], where they have gathered this information based on self-declaration of the Lok Sabha candidates themselves. The total male MPs within BJP and Non-BJP are respectively 6.3 times and 5.6 times more than the total female MPs.

Similarly, we collected information about the different positions held by the MPs and whether they had held a cabinet position at least once in their current or past tenure in Lok Sabha. We counted both Cabinet ministers as well as Ministers of State, that is anyone on the council of ministers, as having held a cabinet position. We found that one-third of BJP MPs and one-fifth of Non-BJP MPs have held cabinet positions at least once. Finally, we also control for the linguistic differences that might influence Twitter networks due to India's multilingual mode of interaction both offline and online. We considered the language an MP most tweeted in as a control for regression analysis. Most MPs tweet in one of 12 languages (English or one of 11 regional languages). 5 MPs in our sample tweeted mostly in code-mixed language — English mixed with a regional language. Within the BJP, 56% and 28% of the MPs tweeted mostly in Hindi and English respectively. However, English is the most tweeted language within Non-BJP, with close to 30% of the MPs preferring that to others.

3.1 Network Measures

We measure three structural properties of the following network of MPs - reciprocity, PageRank and betweenness centrality [15, 125] - to understand how caste as social media capital could manifest online among MPs. More details on these measures can be found in the appendix.

PageRank centrality measures how "central" or important an actor is in the network. While importance can imply many functions, in this case, for each node, we are interested in the volume of incoming *following* connections from its alters and also the importance or "status" of these alters. An ego with high incoming connections, especially from other important nodes, has greater control over the kind of information that is passed onto the network [41, 43]. Combined with caste information, this property could reveal if MPs of a certain caste are considered as important to follow and could expose those who are excluded from following.

Betweenness centrality is defined as the extent to which an ego falls in the shortest paths between different pairs of nodes. It measures the bridging behaviours of nodes, and the greater the value of betweenness for an MP, the more people in the network depend on them to make connections with other MPs [40]. Comparing the betweenness of different castes could shed light on the extent of disruption that can be caused by removing MPs of particular castes in the communication between different parts of the network. Further, integrating knowledge of in-degree and out-degree information in the relations between caste and betweenness could help us further distinguish two kinds of bridging positions that caste groups could play: (a) bridging actors in the network by providing common information and (b) connecting through exposure to information coming from disparate sub-networks [48].

While previous work on *reciprocity* mostly focus at the network level [42, 103], we measure this relationship at the individual level as the proportion of *following* connections that are reciprocal to the total alters an individual follows. Reciprocity in *following* could indicate a wide range of social properties such as trust, sharing interests, opinions and indeed ideologies. Further, studies have shown that people higher up in a power structure or belonging to higher "social status", tend to get reciprocated more [24, 32, 71].

4 INFLUENTIAL POSITIONS

4.1 Comparison of Average PageRank Centrality Across Caste

We first explore the relation between PageRank centrality and caste by examining their distribution for each caste and how the scores differ between pairs of castes on average. As discussed previously, we make the comparison between castes within BJP and Non-BJP independently, to distinguish the effect of caste hierarchy between the current ruling party (BJP) and the rest(Non-BJP.) We expect that a pairwise comparison of the average trend in PageRank sheds light on if and how castelessness of upper castes might manifest into social capital as claimed by social theorists [29].

Figure 2 shows the distribution of log-scaled PageRank centralities of various castes within each party. The distribution in linear scale is very skewed. Some castes, such as the *Brahmins* in BJP and Non-BJP, have approximate log-normal distribution of PageRank. On the other hand, centralities of most other castes appear bimodal but with a shorter right peak. This indicates the presence of few highly influential MPs within each caste. Further, it can be observed that the height of the peaks are more uneven within Non-BJP, highlighting that there are only few influential MPs within Non-BJP, compared to BJP.

We then use the geometric means (`GM`) and geometric standard deviations (`GStd`) to compare the average trend of PageRank distributions for each caste group. We chose the geometric mean because a simple median ignores extreme values and because the geometric mean offers a compromise where they both essentially become equivalent as the distribution becomes log-normal. The network measures, such as PageRank, rely on the information of other nodes in the network and hence are not independent. Thus, standard statistical assumptions about independent observations and data distributions do not hold. Similar to other studies comparing network properties [37, 99], we resort to permutation tests to compute the significance of the difference between geometric means. We randomly swapped the positions of MPs in the network 10,000 times and estimated the difference in `GMs` between two groups in each trial. Following this, we compared this distribution of differences to the observed difference in `GMs`.

We report max-T adjusted p-values to limit Family Wise Error Rate (FWER) when comparing multiple hypotheses [34]. Finally, we also compare the geometric standard deviations of the distributions as a ratio (like a F-statistic) using a similar permutation test. Figure 3 shows the comparison for each pair of castes, both within BJP and Non-BJP.

Within the BJP. *Brahmins* hold more advantageous structural positions in the network than lower-caste MPs and thus exert greater influence in information diffusion and enjoy higher social capital. In fact, *Brahmins* also have higher `GM` PageRank than *Intermediary Castes*. Though the

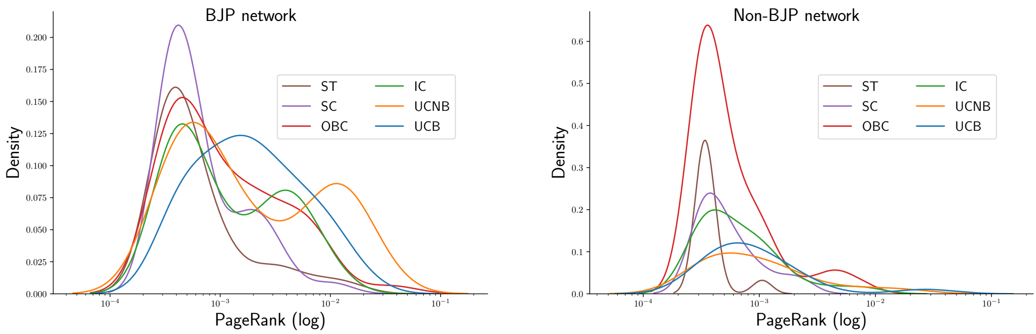
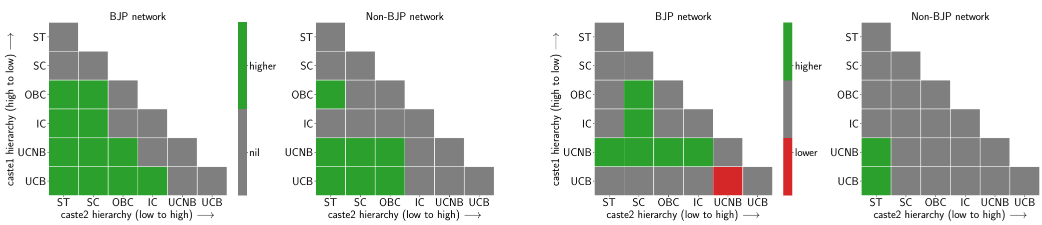


Fig. 2. **PageRank distributions for BJP and Non-BJP in logarithmic scale**



(a) Geometric Mean (b) Geometric Standard Deviation

Fig. 3. **Pairwise comparison of geometric means of PageRank scores for BJP and Non-BJP**

strength of *Brahmins* is commensurate with other castes, they are followed by a relatively higher number of MPs, including other most followed MPs in the network, thus scoring high mean PageRank centrality. Further, Figure 2 shows that *Brahmins* are the only category that has a unimodal distribution with higher mean than almost all castes, implying the absence of groups within the caste with sharp differences in PageRank. *Upper-Caste Non-Brahmins*, on the other hand, have the largest variance of all castes and has higher means than all lower-caste MPs. *Scheduled Castes* and *Scheduled Tribes* are placed at a significant disadvantage where they are not followed by many, thus having the least control over what information they consume or broadcast.

Within the Non-BJP. Both *Brahmins* and *Upper-Caste Non-Brahmins* have higher mean PageRank within Non-BJP in alignment with the upper-caste dominance within BJP. Further, in addition to having lowest mean, *Scheduled Tribes* seem to have the least variance in PageRank than the two most dominating upper castes, making *Scheduled Tribes* the worse-off caste within Non-BJP.

4.2 Does PageRank relate to successful Information Propagation?

In this section, we explore if occupying advantageous positions (e.g. high PageRank) translates into successful propagation within the network for MPs of different castes as measured by the frequency at which they are retweeted. To this end, we examined the retweet network of the MPs to analyze how much one gets retweeted by fellow MPs. Retweets on Twitter could indicate a wide range of functions including one's interest in broadcasting or publicly acknowledging a message [18, 63]. We use weighted in-degree centrality to compute the strength of incoming retweets from other MPs in the network, as a method to measure successful broadcasting. We denote this measure as `RT-indegree`.

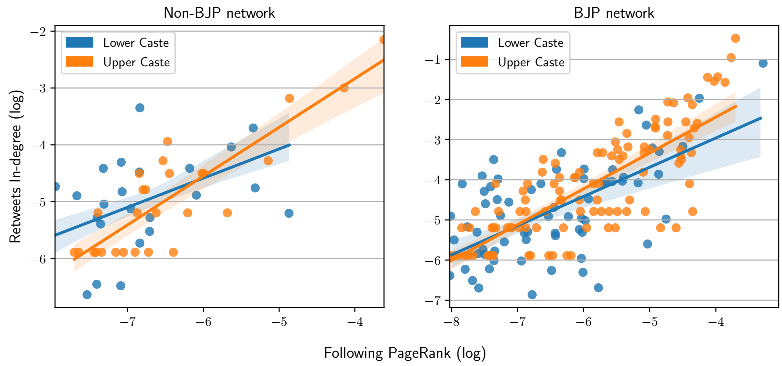


Fig. 4. **Relation between Following PageRank and Retweets In-Degree. The plot shows the relationship for 223 MPs only (out of 434), as 100 out of 150 Non-BJP MPs and 111 out of 284 BJP MPs did not get retweeted at all by other MPs.**

To find the relationship between PageRank and `RT-indegree` and how it differs for each caste, we first sought to run a linear regression with all the castes. However, due to the small number of MPs per caste, we club them into two groups in the regression: (a) *Brahmins*, *Upper-Caste Non-Brahmins*, and *Intermediary Castes* as upper-caste and (b) *Other Backward Castes*, *Scheduled Castes*, *Scheduled Tribes* as lower-caste. We use permutation tests for regressions, using R package `lmPerm` [126], since standard statistical assumptions about independent observations and data distribution do not hold for network data. We model `RT-indegree` as the dependent variable and include PageRank and the binary caste categories as independent variables. We log-transform both `RT-indegree` and PageRank to address the skewness of the variables and bring them to similar scales. Further, we are constrained to use the data of only 223 MPs (out of 434) for this analysis since the remaining MPs did not get retweeted at least once by any other MPs in the network.

We find that there is a strong correlation between PageRank and RT-indegree ($pearsonr = 0.78$) both within BJP and within Non-BJP in the interaction design as well. This shows that occupying influential positions within both BJP and Non-BJP are correlated with being influential in terms of broadcasting information. However, there is no significant difference in the additive individual effects of caste. This implies that the upper-caste MPs are not likely to have higher RT-indegree than lower-caste when controlled for PageRank. However, we sought to find if there is a difference in the amounts of retweets received with increase in PageRank between the upper and lower castes. So we introduce an interaction effect between PageRank and caste-category to examine the interaction effect on the number of retweets. Figure 4 shows the linear relationship by caste categories and the table 2 shows the coefficients.

We find that while the rate of increase in RT-indegree with PageRank does not differ significantly between upper-caste and lower-caste MPs within BJP, the difference is significant within networks of Non-BJP ($coef. = 0.3444, p - value = 0.0124$). In particular, only within Non-BJP, upper-caste MPs receives more retweets compared to lower-caste with an increase in PageRank. We also examined the robustness of the effects by introducing several control variables — gender, cabinet-status, age of Twitter account, and most tweeted language — and found that the relation between caste-category, RT-indegree, and PageRank within both BJP and Non-BJP remains the same. In table 2, the coefficients for some of the languages are not available when the MPs do not tweet in those languages. Due to the differences in languages tweeted by BJP and Non-BJP MPs, the default reference values for *Lang* also differ between the models for BJP and Non-BJP.

Independent Variables	Model: BJP (no-controls)	Model: BJP (with-controls)	Model: Non-BJP (no-controls)	Model: Non-BJP (with-controls)
PageRank	0.729***	0.6654***	0.513***	0.3282*
	(5000)	(5000)	(5000)	(2769)
Upper-Caste	0.169	0.1222	-0.169	-0.1396
	(525)	(51)	(300)	(299)
PageRank x Upper-Caste	0.165	0.1670	0.344*	0.4636***
	(938)	(807)	(2847)	(5000)
Gender:Male		0.1438***		-0.0815***
		(5000)		(5000)
Cabinet:True		0.0286		-0.2932
		(51)		(703)
Account-Age		8.449e-05		9.192e-06
		(684)		(51)
Lang:Bengali		-0.3245		
		(51)		
Lang:English		-0.4440***		-0.4041***
		(5000)		(5000)
Lang:Hindi		-0.5282***		0.3036
		(5000)		(110)
Lang:Kannada		-0.9428*		
		(5000)		
Lang:Marathi		-0.6288		-0.2884*
		(81)		(3248)
Lang:Telugu		-0.8601		
		(1569)		
Lang:Tamil				-0.3041***
				(5000)
Lang:Mixed				0.0719
				(278)
N	173	173	50	50
R^2	0.6049	0.5883	0.676	0.6773

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 2. **Results of Permutation regression in R. `RT-indegree` is the dependent Variable. PageRank and RT-indegree are log-scaled and Upper-Caste is a dummy variable indicating the caste category. Models with control variables are in third and fifth columns. Gender and Cabinet are binary variables. Account-Age is a continuous variable denoting the age in days. *Lang* is a dummy encoded multi-valued categorical variable. The numbers in parenthesis indicate the total number of iterations required for convergence**

Prior studies have shown that the ruling BJP is more effective in promoting itself and in conducting coordinated political messaging [81]. This aligns with our finding that MPs of both the caste categories within BJP receive higher retweets if they are influential within the party. Whereas Non-BJP is a heterogeneous group comprising multiple parties with less coordination, caste split thereby becomes more apparent. However, it should be noted that RT-indegree is computed for the overall time period concerned. So correlating the support received in retweets with important events, topics of the tweets, and the frequency of tweeting could reveal more information about the difference between upper-caste and lower-caste MPs, which we leave to future work.

5 BRIDGING CAPITAL

We observe that 337 (77%) Lok Sabha MPs have non-zero betweenness centrality. Given the large fraction of MPs with zero betweenness, we first explore the proportion of MPs with zero betweenness value across caste to relate disadvantaged bridging positions with caste. Figure 5 shows the

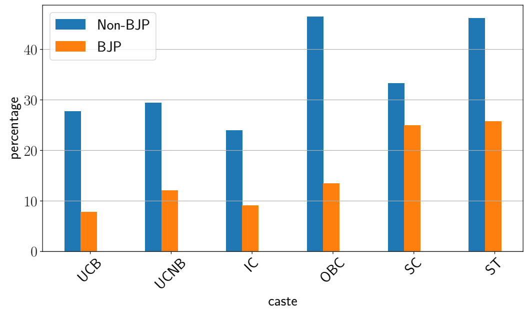


Fig. 5. **Proportion of MPs with zero betweenness or bridging capital in each caste across two parties**

proportions. We find that the proportion of upper-caste BJP MPs with zero betweenness is less than 10% while more than 25% of *Scheduled Castes* and *Scheduled Tribes* BJP MPs have zero betweenness. On the other hand, within Non-BJP, more than 25% of MPs from all castes have zero betweenness. In particular, more than 50% of MPs from the lower castes, *Other Backward Castes* and *Scheduled Tribes*, have zero betweenness. This shows that the difference in occupying significant bridging positions between upper-caste and lower-caste MPs is relatively large in BJP compared to Non-BJP.

5.1 Comparison of Average Betweenness Centrality Across Castes

Similar to comparing the mean PageRanks in the section 4.1, we do a pairwise comparison of the geometric means and standard deviations of betweenness centralities between each pair of castes. Figure 7 shows the mean comparison after the permutation tests and figure 6 shows the distribution of betweenness across castes and parties.

Within the BJP. The betweenness distribution of castes within BJP indicates that *Scheduled Castes* are at a particular disadvantage compared to all other castes. In particular, Figure 7 shows that both the dominating upper castes, *Brahmins* and *Upper-Caste Non-Brahmins*, have a significantly higher mean betweenness than *Scheduled Castes*. Further, *Scheduled Castes* also have a significantly lower mean than the lowest caste in the caste hierarchy, *Scheduled Tribes*, making the former most disadvantaged in terms of bridging the network and controlling information flow within BJP. Further, it can be observed that there is a peak towards the lower end of betweenness for *Intermediary Castes*, indicating that few MPs of that caste have a very low betweenness compared to all other castes. This is also reflected in `GStd` comparison in Figure 7 where we observe that *Intermediary Castes* have the highest variance than all other castes (except *Scheduled Tribes*) whose distribution is approximately unimodal.

Within the Non-BJP. Contrary to what was observed for *Scheduled Castes* MPs in BJP, we find that within Non-BJP they play a dominant role in bridging different actors in the network – they have significantly higher `GM` than *Brahmins*, *Other Backward Castes*, and *Intermediary Castes*. Further, the distributions in Figure 6 shows that most of the *Scheduled Castes* MPs have a very high betweenness value and are skewed towards the left. *Upper-Caste Non-Brahmins* is the only caste within Non-BJP that has a relatively similar distribution of betweenness with *Scheduled Castes*. Though *Scheduled Tribes* MPs's betweenness is distributed towards the lower end, there are only 7 *Scheduled Tribes* MPs with non-zero betweenness within Non-BJP which defies any valid statistical inference. Further, we observe that *Other Backward Castes* have MPs with the most diverse betweenness values. Figure 7 also shows that their variance is significantly larger than most other castes. Finally, in

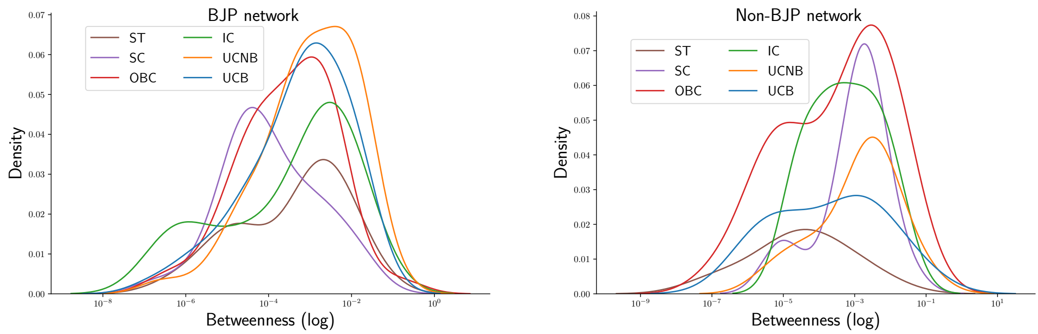
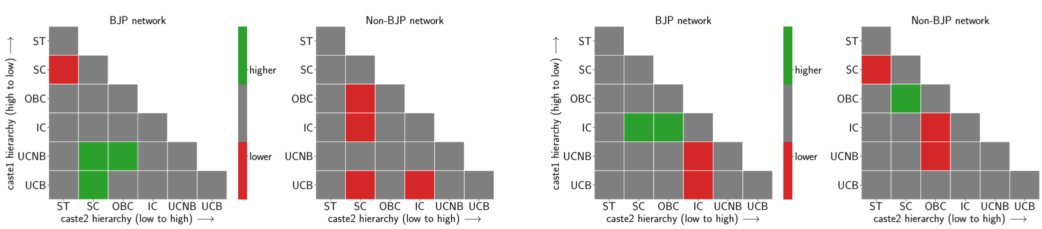


Fig. 6. **Betweenness distributions for BJP and Non-BJP in logarithmic scale**



(a) Geometric Mean

(b) Geometric Standard Deviation

Fig. 7. **Pairwise comparison of geometric means of betweenness for BJP and Non-BJP**

contrast to the dominance of *Brahmins* in PageRank centrality that we saw in BJP, they have a relatively flatter distribution of betweenness within Non-BJP.

5.2 Different types of Bridging Positions

While MPs of high betweenness essentially play the role of bridging different pairs of nodes, since we are working with a directed network, betweenness centrality alone is not sufficient to study the direction of information flow within the network — a node can achieve high betweenness by having high in-degree, high out-degree, or both. Thus, integrating the information about the in-degree and out-degree of the nodes in the relations between caste and betweenness could help us further distinguish different kinds of bridging positions that caste groups could play [48]. In particular, when an MP has a high betweenness centrality but also high in-degree and low out-degree, it indicates that they are providing information that is common and relevant to different pairs of nodes in the network. On the other hand, if someone has high out-degree, low in-degree and high betweenness, it highlights that they are connecting the network by receiving information coming from disparate sub-networks [48]. The two types of bridging positions discussed above are unique in how they connect the network, and in this section, we seek to examine if these differences are associated with caste.

In table 3 and 4, we compare how the in-degree and out-degree differ between lower and upper castes for MPs above a particular threshold of betweenness. We do this analysis for BJP and Non-BJP separately. We normalize (min-max scaled) the measures to bring them all on a common scale. We compare the measure for different thresholds for high betweenness for robustness. The values in the first four columns of table 3 refer to BJP MPs who have betweenness above 50% of the sample and values in the subsequent columns refer to a threshold of 75%. While ideally we expect to examine the difference for each caste individually, the sample sizes drop drastically with high betweenness making statistical inferences challenging. It can be observed from that table that at both thresholds of high betweenness, lower-caste MPs tend to have lower in-degree on average compared to upper-caste MPs. On the other hand, the out-degree is equal to in-degree at a threshold of 50% and greater at a higher betweenness threshold of 75%. These observations indicate that the lower-caste MPs within BJP connect different regions of the network by reaching out more than by providing common information to parts of the network.

	thres=0.5				thres=0.75			
Caste-Category	N	in-degree	out-degree	difference	N	in-degree	out-degree	difference
upper-caste	79	0.143	0.284	-0.15	46	0.232	0.338	-0.111
lower-caste	42	0.103	0.284	-0.17	14	0.135	0.500	-0.247

Table 3. **Difference in Bridging Positions for BJP MPs. The first column is caste, and the second column is sample size. The next three column corresponds to in-, out-, and median of differences between in- and out-degrees for MPs who have betweenness above the 50th percentile (median). Similarly, the next set of three columns corresponds to MPs with betweenness above 75th percentile.**

	thres=0.5				thres=0.75			
Caste-Category	N	in-degree	out-degree	difference	N	in-degree	out-degree	difference
upper-caste	22	0.037	0.083	-0.011	13	0.057	0.083	0.025
lower-caste	26	0.078	0.155	-0.044	11	0.123	0.321	-0.163

Table 4. **Difference in Bridging Positions for Non-BJP MPs. First table: The first column is caste, the next three column corresponds to in-, out-, and median of differences between in- and out-degrees for MPs who have betweenness above the 50th percentile (median). Similarly, the next set of three columns corresponds to MPs with betweenness above 75th percentile.**

6 RECIPROCITY

We measure individual-level reciprocity, which quantifies the tendency of a node to form mutual connections with another. Having a reciprocal relation between two nodes could indicate a wide range of functions from cooperation, trust, status similarity to exchange of ideas.

6.1 Comparison Of Average Reciprocity Across Castes

Figure 9 shows the pairwise comparison of geometric means and standard deviations of reciprocity. Figure 8 shows their distributions by caste and party. We use geometric means and standard deviations for reasons described in previous sections.

Within the BJP. *Brahmins* MPs have a significant advantage over *Scheduled Castes* and *Scheduled Tribes* MPs in terms of getting average reciprocal follow links from other MPs in the network. Further, *Brahmins* and *Upper-Caste Non-Brahmins*, are the only castes that have a significant difference in reciprocity over another caste, indicating the dominance of the top two upper castes. The distribution plot also shows that while *Scheduled Castes* have their peak value of reciprocity towards left or smaller values compared to other castes, *Scheduled Tribes* seems to have a flatter distribution. These are also reflected in Figure 8-b, where the `GStd` of *Scheduled Tribes* is significantly

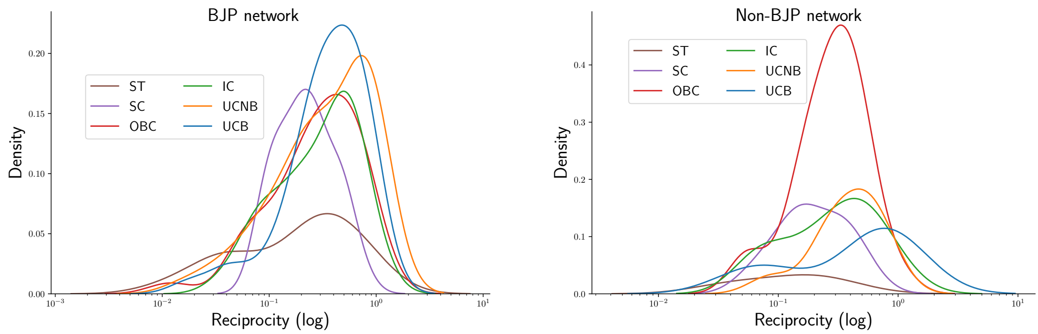
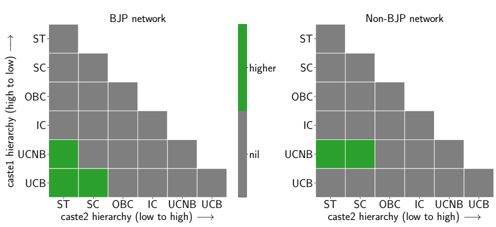
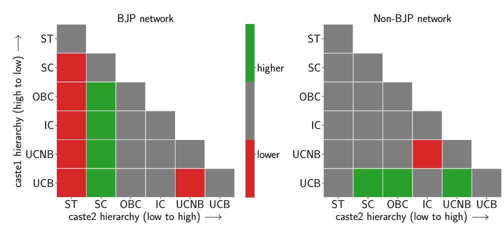


Fig. 8. **Reciprocity distributions for BJP and Non-BJP in logarithmic scale**



(a) Geometric Mean



(b) Geometric Standard Deviation

Fig. 9. **Pairwise comparison of geometric means of reciprocity for BJP and Non-BJP**

higher than all the castes within BJP, and the `GStd` of *Scheduled Castes* is significantly lower than all other castes.

Within the Non-BJP. *Upper-Caste Non-Brahmins* is the only caste that has significantly higher mean reciprocity than any other caste, their `GM` is higher than the two castes lowest in hierarchy - *Scheduled Castes* and *Scheduled Tribes*, similar to what was observed for BJP. Note that the *Upper-Caste Non-Brahmins* MPs form only about 10% of Non-BJP MPs, but still have an advantage over lower-caste MPs in terms of reciprocity. The propensity or ability to form mutual links by *Upper-Caste Non-Brahmins* MPs is significantly greater than of *Scheduled Castes* and *Scheduled Tribes*, indicating that perhaps the social capital and other factors affecting lower-caste MPs are shaping how they can effectively be excluded by *Upper-Caste Non-Brahmins* MPs in the network.

In summary, these findings within BJP and Non-BJP denote that if an upper-caste MP decides to listen to someone in the network, they are more likely to be heard in return than lower-caste MPs; implying that lower-caste MPs are not heard as widely in the network as their counterparts from upper castes.

6.2 Relation with PageRank and betweenness

We observed that some of the upper and lower castes differ in reciprocity as well as in occupying influential (using PageRank) and bridging (betweenness) positions. We expect that someone with structurally advantageous positions could have higher reciprocal links. However, the relationship between occupying strong bridging positions and forming reciprocal ties is not straightforward as the notion of trust with someone bridging different sets of nodes depends on the type of network and reasons why the individual makes connections. One way to tackle this question at scale from a networks perspective is to run a regression with reciprocity as the dependent variable and the two

Independent Variables	M1: BJP	M2: BJP	M3: BJP (no-controls)	M3: BJP (with-controls)	M1: Non-BJP	M2: Non-BJP	M3: Non-BJP (no-controls)	M3: Non-BJP (with-controls)
PageRank	0.999^{***}		0.917^{***}	0.9753^{***}	0.950^{***}		0.736^{***}	0.7357^{***}
	(5000)		(5000)	(5000)	(5000)		(5000)	(5000)
Betweenness		0.849^{***}	0.097^{*}	0.0836.		0.687^{***}	0.2043^{**}	0.1706
		(5000)	(5000)	(1344)		(5000)	(5000)	(278)
Upper-Caste	-5.563	24.333	-4.852	0.6979	21.816	-10.909	-14.078	-13.6023
	(51)	(680)	(51)	(51)	(78)	(77)	(199)	(51)
Gender:Male				1.1219^{***}				-7.0602
				(5000)				(332)
Cabinet:True				0.2759				-38.5591
				(51)				(425)
Account-Age				-0.0100				0.00216
				(1082)				(96)
Lang:Bengali				62.1545^{*}				
				(5000)				
Lang:English				1.2863^{***}				24.7872^{*}
				(5000)				(1982)
Lang:Gujarat				-81.9345				
				(408)				
Lang:Hindi				31.9572^{***}				9.9510
				(5000)				(555)
Lang:Kannada				33.5366				-7.0602
				(462)				(332)
Lang:Marathi				-30.4752				11.5834
				(51)				(208)
Lang:Oriya				37.7302				35.8211
				(85)				(51)
Lang:Telugu				11.5776				-0.4515
				(51)				(77)
Lang:Tamil								23.3604
								(481)
Lang:Malayalam								44.8281
								(303)
Lang:Mixed				21.8446				51.2326
				(51)				(311)
N	284	284	284	284	150	150	150	150
R^2	0.839	0.637	0.841	0.8371	0.569	0.4802	0.579	0.5467

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table 5. **Results of Permutation regression in R. `Reciprocity` is the dependent Variable. Difference between upper-caste and lower-caste are analysed by controlling for PageRank only (M1), by controlling Betweenenss only (M2) and by controlling both these centralities in M3. All the network measures are in ranks and Lower-Caste is a dummy variable indicating the caste category. Models with control variables are in fifth and last columns. Gender and Cabinet are binary variables. Account-Age is a continuous variable denoting the age in days. *Lang* is a dummy encoded multi-valued categorical variable. The numbers in parenthesis indicate the total number of iterations required for convergence.**

types of centralities - PageRank and betweenness - in addition to caste categories as the independent variables. Further, a more objective approach is to replace the absolute values of these metrics with corresponding *ranks* and do a rank regression, in order to capture the relative effects of orders of PageRank or betweenness on reciprocity

Specifically, we build three models as shown in Table 6. We use permutation tests for regressions using `lmPerm` [126] as we did in section 4.2. We transformed `RT-indegree` and PageRank to logarithmic scales to address skewness. First, with model `M1`, we seek to understand the effect of caste categories on reciprocity by controlling for PageRank only. We observe that, within both BJP and Non-BJP, PageRank is strongly correlated with reciprocity as expected, but the effect of PageRank on reciprocity is not significantly different between upper and lower castes. Similarly, in model M2, we find that betweenness is also highly correlated with reciprocity, though the effect size is smaller than that of PageRank. This indicates that there might be a relation between PageRank and betweenness centralities in forming mutual connections.

In model M3, we include both PageRank and betweenness and examine the difference in effect of these variables on reciprocity between upper and lower castes. We find no significant effects for caste categories. Similar to section 4.2, we examine the above effects in the presence of controls — gender, cabinet-status, age of Twitter account, and most tweeted language in all three models. We show the results only for model M3 for brevity. We find no difference in the effects of betweenness and PageRank on reciprocity when control variables are introduced in models M1 and M2.

However, the results show that the effect of betweenness on reciprocity drops significantly when controlling for PageRank within both BJP and Non-BJP. This indicates that in our network, MPs with high PageRank are more preferred to have reciprocal connections than those with higher betweenness. In particular, the effect of betweenness is almost negligible ($t = 0.098, p-value = 0.04$) showing that bridging functions are not as important in forming reciprocal connections within BJP; the effect becomes further insignificant when additional controls are introduced. Though the effect of caste categories on reciprocity is not significant after controlling for PageRank and betweenness, we observed in previous sections that the upper castes, *Brahmins* and *Upper-Caste Non-Brahmins*, in the network dominate with higher PageRank and hence consequentially, they have higher average reciprocity than *Scheduled Castes* and *Scheduled Tribes* (Figure 9). Looking at the effects of individual castes might show some significant differences in reciprocity between castes but the small sample size of our dataset deters us from undertaking this analysis.

Comparison of ranks. We do an additional exploratory analysis to examine the differences between upper and lower castes in the relation between reciprocity, PageRank, and betweenness. We use PageRank and betweenness ranks to understand the relative difference between occupying influential and bridging positions. Then, we compare this difference in ranks with the reciprocity ranks to examine possible differences between upper and lower castes. Table 6 shows the results by caste category and party. We find that, within BJP, the median PageRank, betweenness, and reciprocity drops for lower castes and the median difference in ranks is significantly more positive for upper castes than for lower castes. This supports our previous arguments that upper castes within BJP have higher PageRank and it might explain their relatively higher reciprocity. Whereas in non-BJP, the median difference in ranks for lower castes is significantly more negative than for upper castes, corroborating with our results in section 6 where we found that *Scheduled Castes* have higher mean betweenness. In summary, while MPs with high PageRank (where upper castes dominate in both parties) are more likely to form greater reciprocal links within both BJP and Non-BJP, MPs with higher betweenness (where *Scheduled Castes* dominate in Non-BJP) relatively have a higher chances of getting reciprocal connections within Non-BJP than within BJP.

	BJP					Non-BJP				
Caste-category	N	PageRank	Betweenness	difference	Reciprocity	N	PageRank	Betweenness	difference	Reciprocity
upper-caste	153	293.6	273.4	20.2	276.2	60	224.6	215.4	9.2	180.9
lower-caste	131	210.5	210.9	-0.3	198.8	90	138.8	159.1	-20.2	120.4

Table 6. **PageRank:Betweenness:Reciprocity - for each party, the first column is caste, the next two column corresponds to median PageRank and betweenness centrality ranks respectively. The third column corresponds to the median of the difference between PageRank and betweenness ranks and the final column corresponds to the reciprocity ranks.**

7 DISCUSSION

Our study analyzes three structural properties of the Twitter network of Members of Parliament in India to understand how caste manifests as social capital in the information economy. We defined social capital within this network as influence (or Pagerank), bridging capital (or betweenness), and reciprocity. Our findings shed light on how the social capital of MPs manifests across differences of caste, party, ideology and the dynastic nature of Indian politics.

7.1 Implications for relations between political parties and caste for social media capital:

We find that trends of Lok Sabha electoral politics being elitist [52] are also reflected in social media as political elites are able to garner more influence across different parties. Caste-level differences in access to different social media capital in the network are further nuanced by their relationships with party and ideology. While political alliances of MPs might change over time, these observations provide a snapshot of how caste relations operate within party structures.

Brahmins and other upper-caste MPs have higher social capital in BJP than lower-caste MPs. BJP distributed half its tickets to upper-caste candidates for Lok Sabha elections of 2019, most of whom got elected. At the same time, BJP tends to draw its support largely from upper-caste and OBC voters, although its appeal is growing across castes [52]. These patterns show how BJP re-configures the idea of political elites on social media as it does in composition of its representatives [52].

The patterns of MPs in non-BJP parties are harder to discern because they are not united under a common strategy like that of BJP, yet we see an overall upper caste advantage continue here. *Scheduled Castes* have a good bridging position in the network of non-BJP parties, but the overall disadvantage of *Scheduled Tribes* MPs is the same as in BJP. A more in-depth analysis of the network and its interactions could determine if this trend emerges due to the fact that some non-BJP parties operationalize their platforms for lower-caste interests and voices. Overall, claims of equity based on religious secularism in other parties fail lower-caste communities when it comes to inclusion in practice.

7.2 Implications for the influence of MPs from different castes in the network:

Non-BJP			BJP		
screen-names	Followers count	Caste	screen-names	Followers count	Caste
RahulGandhi	13975165	*Brahmins*	narendramodi	56804903	*Other Backward Castes*
ShashiTharoor	7542729	*Upper-Caste Non-Brahmins*	AmitShah	19963493	*Upper-Caste Non-Brahmins*
supriya_sule	1019804	*Intermediary Castes*	rajnathsingh	16971939	*Upper-Caste Non-Brahmins*
yadavakhilesh	11741637	*Other Backward Castes*	smritiirani	11037495	*Upper-Caste Non-Brahmins*
HarsimratBadal_	210277	*Other Religion*	drharshvardhan	2243586	*Upper-Caste Non-Brahmins*
ManishTewari	409842	*Upper-Caste Non-Brahmins*	rsprasad	4209709	*Upper-Caste Non-Brahmins*
KanimozhiDMK	446966	*Other Backward Castes*	nitin_gadkari	7036050	*Brahmins*
GauravGogoiAsm	131497	*Other Backward Castes*	KirenRijiju	748819	*Scheduled Tribes*
officeofssbadal	353386	*Other Religion*	nstomar	295348	*Upper-Caste Non-Brahmins*
asadowaisi	1356297	*Other Religion*	gssjodhpur	181658	*Upper-Caste Non-Brahmins*
BhagwantMann	324540	*Other Religion*	ombirlakota	228215	*Upper-Caste Non-Brahmins*
abhishekaitc	321991	*Brahmins*	DrJitendraSingh	446016	*Upper-Caste Non-Brahmins*
ichiragpaswan	114976	*Scheduled Castes*	prahladspatel	284146	*Other Backward Castes*
mimichakraborty	797311	*Brahmins*	arjunrammeghwal	180545	*Scheduled Castes*
hanumanbeniwal	203791	*Intermediary Castes*	DrRPNishank	262720	*Brahmins*

Table 7. **Politicians sorted by PageRank centrality. The PageRank decreases from top to bottom.**

PageRank values are higher for upper-caste MPs both in BJP and Non-BJP parties. In BJP, higher PageRank is also correlated with higher propensity to form mutual connections with other MPs.

This creates a compounding effect of double disadvantage for lower-caste BJP candidates on social media. They have lesser influence or importance in the network of MPs and other MPs are likely to follow them when compared to upper-caste MPs. On the other hand, upper-caste MPs in Non-BJP parties tend to have more retweets with higher PageRank than lower-caste. Overall, we observe lower-caste MPs struggling with building a wide network as well as becoming important in the network.

Over half of the 15 highest ranked politicians in non-BJP parties are children or relatives of a major politician, someone who has established a political party, or served as a head of government. This includes Rahul Gandhi, Gaurav Gogoi, Kanimozhi, Harsimrat Badal, Supriya Sule, Akhilesh Yadav, Abhishek Banerjee, and Chirag Paswan. This new generation of political actors seem to be benefiting from dynastic advantage in politics [120] which have a close relationship with caste in India due to the practice of caste endogamy [8]. These "offline" dynamics seem to be playing a role in their social capital on Twitter.

7.3 Implications for the bridging capital of MPs from different castes in the network

We find that *Brahmins* and *Upper-Caste Non-Brahmins* MPs within BJP tend to be a bridge between MPs of different groups in the network. They are more critical in the network for other MPs who depend on them for information and connectivity with different parts of the LokSabha network. Previous work in CSCW on caste and Twitter has shown that *Scheduled Castes* in BJP tend to retweet upper-caste MPs more [114]. In this study we find that *Scheduled Castes* MPs have the lowest bridging capital in BJP and that overall lower-caste MPs in BJP rely on outgoing connections to other MPs to gain a stronger foothold in the MPs Twitter network. These trends can be a reflection of these MPs trying to gain mobility. Many Dalits attempt to gain mobility in a caste society by trying to assimilate but find themselves alienated from the larger caste-Hindu society [64].

Interestingly, Dalits in Non-BJP parties play a dominating role in bridging other actors in the network, rather *Brahmins* are at a disadvantage. We find that this trend favors them in forming reciprocal relationships in the network over Dalit MPs in BJP. We get an insight into the dynamics of political parties and caste: where social capital in Non-BJP parties is gained through a capacity to connect different sub-networks (bridging capital,) which can be an advantage for lower-caste groups who are at the margins of the society. Whereas in a populist party like BJP, the overall importance of the MP (Pagerank measured by how many other important people are they connected to) is given more weight. This may or may not be a strong offering of lower-caste groups who struggle to reach positions of power and be reciprocally connected with powerful actors.

7.4 Propensity of MPs to form mutual connections and its implications:

We find that, overall, lower-caste MPs are not as widely heard in the network as they don't receive as many follow-backs as upper-caste MPs. The relationship of what begets more mutual relationships with other MPs in the network provides insight into social media capital available to historically disadvantaged communities in politics. *Scheduled Castes* and *Scheduled Tribes* MPs tend to not have social capital from generational access to politics, or generally high political status like upper-caste MPs who have a history of better access to national government bodies and technology/smartphones. The PageRank of key politicians in the BJP illustrates how dynastic politics and importance (Pagerank) come together for lower-caste MPs who make it big. From the 15 highest ranked politicians in table 6 we see that only Arjun Ram Meghwal and Kiren Rijiju belong to the scheduled castes and tribes. Both are members of prominent political families with roots in multiple parties, and Rijiju is from a state in which the ST population is the dominant majority.

Dalits or *Scheduled Castes* MPs in BJP fare even worse than *Scheduled Tribes* MPs, who seem to be able to forge some mutual connections there. Untouchables were one of the last segregated population [64] and this trend against *Scheduled Castes* MPs acts as a form of digital apartheid in the BJP network. While there may be incentives among politicians to disassociate themselves from certain castes or communities in local elections, there is no evidence that this has been done in a systematic way between politicians in Lok Sabha as there is generally collegiality within parties, at least publicly. In this case, we can only assume that the lack of following is organic and possibly driven by unconscious bias and/or related to the relatively higher centrality of upper-caste MPs.

7.5 Implications for inequality and social computing

Our study has implications for both the in-depth study of Indian politics and for the methodological approaches that help understand caste inequality on social media in the context of India. Previous work in CSCW on caste and Twitter has shown that upper-caste MPs engage with each other more than they do with lower-caste MPs [114]. This also means that upper-caste MPs continue becoming more and more important in the network with each other's support and form information bottlenecks. Our findings show that upper-caste MPs don't need to rely on outreach to have important bridging positions. With a high degree of incoming follow signals resulting in higher bridging capital, they are nodes from which information flows to others. On the other hand, with a high degree of outgoing follow signals for higher bridging capital, lower-caste MPs rely on exposure to information from other MPs and sub-networks. This clearly indicates the powerful position enjoyed by upper-caste MPs in terms of the flow of information and bridging capital than those in lower-caste communities who derive power by depending on connections with other people in the network.

The implications on *Scheduled Castes* and *Scheduled Tribes* communities is severe as we witness a form of "chilling effect" in almost all cases by the network effects of structural advantage for upper castes. These results indicate that equal opportunity of representation for *Scheduled Castes* and *Scheduled Tribes* communities through reservations in LokSabha has not necessarily translated into access to social media capital similar to upper-caste MPs. This is regardless of whether they decide to align with BJP's promise of integrating and supporting them under a single "Hindu" banner or align with Non-BJP parties that are caste-sympathetic and secular in their political ideology. Thus, despite the messages of equality within the Hindu community, the reality of how lower-caste MPs navigate the political networks on Twitter and their structural disadvantage gives a window into how they continue to face implicit or unconscious bias in the world of social media from other MPs. We see a manifestation of hidden social media capital that is deeply intertwined with a caste based hierarchy in the world of social computing.

8 LIMITATIONS AND FUTURE WORK

We acknowledge the limitations in our methodology and note areas for further improvement in our study. First, we decided to only focus on the Lok Sabha MPs to understand how caste operates in Indian politics on Twitter. Expanding our analyses to other politicians and actors who engage strongly with politics and politicians, such as influencers, celebrities, or media houses could help generalize and interpret observations in more detail. The study is also limited by the size of the dataset, just 482 MPs who have a presence on Twitter. We rely on some simplification of "political party" as well as "religion" and "caste."

We simplified political parties into BJP and Non-BJP which occludes the dynamics of individual parties and how they in turn affect the LokSabha networks. This does not imply that BJP is the only right wing party; nor is it to imply that those in non-BJP are left-wing. There are numerous regional parties with their own constituents and ideologies in India. The binary can be misleading and we clarify our reasoning for the choice of labels and groupings in Section 3. This is a functional categorization since BJP and its allied political parties make up 60% of MPs on Twitter. It gives insights at the level of macro categories of political parties and their alliances within the parliamentary network.

We excluded MPs from religions other than Hinduism in our analysis but caste in India exists across religions [3, 36, 75, 110]. Their lack of representation in the Indian parliament would lower the power of statistical inference in this quantitative study [19]. We also grouped lower and upper castes for regression analysis because we had fewer MPs in each caste group within each political party. Our study could have benefited from rigorous construction of databases on the caste of local politicians for a nuanced understanding of social media capital at scale. Curating caste annotation is a time-consuming political act involving tactful manual labour. Despite their relatively higher socio-economic capital and over-representation in different professions or spaces, the *General* Category or upper castes are unaccounted for in terms of their *jati* or sub-caste differences. Political resistance to the decennial caste census in India perpetuates the myth that they are casteless [30, 31, 123]. For more rigorous computational studies of caste and social media, it is important to dispel the myth of castelessness of upper castes with data.

Our analysis is limited by the fact that we have not considered the evolution of networks across castes over time and parties. We chose the time period of the study retrospectively based on socio-political events of consequence for the MPs in India. We could only work with a snapshot as Twitter restricts the supply of the data with free developer API. Without the temporal information, we could have lost important nodes that could have been influential at some point in time but dropped off the network for reasons like account suspension. Future studies can take a more experimental approach leading up to General elections in India to study the evolution of these structural properties over time. It could provide more insights on when and how MPs of certain castes dominate or utilize social media capital, when their influence changes, and how it relates with important political or social events.

The measurement of social capital in networks is a heavily debated and disputed science with a myriad of competing arguments and approaches. In our study, we relied on a set of literature and prior work that gave us a handle on how to approach this question in a novel setting. We chose the particular metrics of PageRank, betweenness and reciprocity for their relevance and potency in explaining the nature of relations of the caste system in India. While we believe that a study of social networks is useful to understand implicit bias and invisible relations of power, we do not claim generalizability of these metrics to examine social capital contexts that don't involve caste. Each network of relations needs to be understood with its unique history in a particular context to study social capital. What we see here are defining metrics of network capital in the largest electoral system in the world which we believe are critical to examine and understand caste and politics on social media.

Lastly, mechanisms of IT cells and social media managers mediate political communication on Twitter in India. They complicate the interpretations of these relations as a realpolitik dynamic between MPs. Our work interprets social media networks as "what you see is what you get." This is mainly because caste relations online are otherwise harder to capture and study due to their implicit nature. The strength of this method is balanced with its limitations. While it is not possible to ascribe intention based on secondary social media research, this study sets the stage for deeper qualitative work on what motivates the choices of engagement with other politicians by MPs and their social media teams. We control for some variables in our analysis but there are possibly more confounds to control for in future work, like: digital literacy of politicians, management of accounts by staff, switching of parties by MPs closer to elections, or the choice of medium for connecting with other political members and constituents. Our work is limited by the nature of our methodology that relies on "follow" networks to interpret who listens to whom and the overall influence and control of an MP over the information in a network. Yet, metrics like retweets, likes, and the text of the tweets themselves might have more insight to offer into caste relations between politicians online, especially when we control for other sociological factors like gender, language, etc. We hope that our work encourages studying social media communications for signaling of relations between people in powerful positions from different castes or communities. More importantly, we want to show how social media networks can serve as a window to infrastructures of power and their co-production in socio-technical societies. Future studies can use similar methodologies to shed light on social media capital of members from different castes in other institutions of consequence like media, academia, entertainment, government bureaucracy, corporations, etc.

9 CONCLUSION

An important characteristic of marginalization that is seen in exclusionary cultures throughout the world [35], and specifically noted on caste lines in India [108], is rendering the marginalized invisible. Social media, often cited as a tool for inclusion, offers a unique window into the networks of covert exclusion. Our findings have methodological consequences for the ways social inequality is understood and studied in the sociotechnical and CSCW literature. Our work exposes how organic networks of power are reinforced through social networks in actions as simple as following or retweeting someone on Twitter. Through this prism, we see the exclusion of lower-caste politicians from networks as an indicator of their marginality in political and party systems, rather than as victims of an orchestrated or overt exercise of social media exclusion.

This one of the first steps in characterizing the nature of caste relations that operate under the guise of castelessness, and how they can be understood through network analysis in socio-technical systems. We acknowledge that the aggregate nature of our findings at the meso-level leaves room to speculate on the emergent nature of inter- and intra-caste relations at the micro level. We hope these findings set the stage for a more detailed study of caste networks and future work on critical examination of social capital and its relationship with caste in the digital economy.

REFERENCES

[1] 2019. . Lokniti – Centre for the Study of Developing Societies (CSDS). https://www.csds.in/uploads/custom_files/Report-SMPB.pdf

[2] Crystal Abidin. 2017. Vote for my selfie: Politician selfies as charismatic engagement. In *Selfie Citizenship*. Springer, 75–87.

[3] Imtiaz Ahmad. 1978. *Caste and social stratification among Muslims in India*. South Asia Books.

[4] Saifuddin Ahmed, Kokil Jaidka, and Jaeho Cho. 2016. The 2014 Indian elections on Twitter: A comparison of campaign strategies of political parties. *Telematics and Informatics* 33, 4 (2016), 1071–1087.

[5] Dayanandan Ajit, Han Donker, and Ravi Saxena. 2012. Corporate boards in India: blocked by caste? *Economic and Political Weekly* (2012), 39–43.

[6] Akhil Alha. 2018. The Other Side of Caste as Social Capital. *Social Change* 48, 4 (2018), 575–588.

[7] BR Ambedkar. 1936. Annihilation of Caste: Speech Prepared for the Annual Conference of JPTM of Lahore but Not Delivered. *BR Kadrekar* (1936).

[8] Babasaheb Ambedkar. 2011. *Castes in India*. Prabhat Prakashan.

[9] Abhijit Banerjee, Marianne Bertrand, Saugato Datta, and Sendhil Mullainathan. 2009. Labor market discrimination in Delhi: Evidence from a field experiment. *Journal of comparative Economics* 37, 1 (2009), 14–27.

[10] Marguerite Ross Barnett. 2015. *The politics of cultural nationalism in South India*. Princeton University Press.

[11] Naveen Bharathi, Deepak V Malghan, and Andaleeb Rahman. 2019. Village in the City: residential segregation in urbanizing India. *IIM Bangalore Research Paper* 588 (2019).

[12] Swati Bhasin. 2020 (accessed May 31, 2020). Why India Would Remember 2019: A Quick Rewind Of Major News Events. https://www.ndtv.com/india-news/why-india-would-remember-2019-a-quick-rewind-of-major-news-events-2155717.

[13] Shreya Bhattacharya. 2020. *Essays on Identity and Social Interactions*. Ph.D. Dissertation.

[14] Phillip Bonacich. 1972. Factoring and weighting approaches to status scores and clique identification. *Journal of mathematical sociology* 2, 1 (1972), 113–120.

[15] Stephen P Borgatti and Martin G Everett. 2006. A graph-theoretic perspective on centrality. *Social networks* 28, 4 (2006), 466–484.

[16] Stephen P Borgatti, Candace Jones, and Martin G Everett. 1998. Network measures of social capital. *Connections* 21, 2 (1998), 27–36.

[17] Geoffrey Bowker and Susan Leigh Star. 1999. *Sorting things out*. Vol. 297. Cambridge, MA: MIT Press.

[18] Danah Boyd, Scott Golder, and Gilad Lotan. 2010. Tweet, tweet, retweet: Conversational aspects of retweeting on twitter. In *2010 43rd Hawaii International Conference on System Sciences*. IEEE, 1–10.

[19] Katherine S Button, John PA Ioannidis, Claire Mokrysz, Brian A Nosek, Jonathan Flint, Emma SJ Robinson, and Marcus R Munafò. 2013. Power failure: why small sample size undermines the reliability of neuroscience. *Nature Reviews Neuroscience* 14, 5 (2013), 365–376.

[20] Sunandan Chakraborty, Joyojeet Pal, Priyank Chandra, and Daniel M Romero. 2018. Political tweets and mainstream news impact in India: A mixed methods investigation into political outreach. In *Proceedings of the 1st ACM SIGCAS Conference on Computing and Sustainable Societies*. 1–11.

[21] Drupa Dinnie Charles, Azhagu Meena, Simiran Lalvani, Syeda Zainab Akbar, Divya Siddharth, and Joyojeet Pal. 2020. Performing gender, doing politics: social media and women election workers in Kerala and Tamil Nadu. In *Proceedings of the 2020 International Conference on Information and Communication Technologies and Development*. 1–11.

[22] Anumeha Chaturvedi. 2017. How India emerged as Twitter's fastest growing market in terms of daily active users. *Economic Times* (2017).

[23] Swati Chaturvedi. 2016. *I am a troll: Inside the secret world of the BJP's digital army*. Juggernaut Books.

[24] Justin Cheng, Daniel M Romero, Brendan Meeder, and Jon Kleinberg. [n.d.]. Predicting reciprocity in social networks. In *2011 IEEE Third International Conference on Privacy, Security, Risk and Trust and 2011 IEEE Third International Conference on Social Computing*. 49–56.

[25] Pradeep Chhibber and Rahul Verma. 2019. The rise of the second dominant party system in India: BJP's new social coalition in 2019. *Studies in Indian Politics* 7, 2 (2019), 131–148.

[26] CS Crawford and George Ritzer. 2005. Encyclopedia of Social Theory. A: Actor Network Theory. Vol. 1.

[27] Naga Lakshmi Damaraju and Anil K Makhija. 2018. The role of social proximity in professional CEO appointments: Evidence from caste/religion-based hiring of CEOs in India. *Strategic Management Journal* 39, 7 (2018), 2051–2074.

[28] Marc Esteve Del Valle and Rosa Borge Bravo. 2018. Echo chambers in parliamentary twitter networks: The catalan case. *International journal of communication* 12 (2018), 21.

[29] Satish Deshpande. 2013. Caste and Castelessness: Towards a Biography of the'General Category'. *Economic and Political Weekly* (2013), 32–39.

[30] Satish Deshpande and Mary E John. 2010. The politics of not counting caste. *Economic and Political Weekly* (2010), 39–42.

[31] Satish Deshpande and Nandini Sundar. 1998. Caste and the census: Implications for society and the social sciences. *Economic and Political Weekly* (1998), 2157–2159.

[32] Andreas Diekmann. 2004. The power of reciprocity: Fairness, reciprocity, and stakes in variants of the dictator game. *Journal of conflict resolution* 48, 4 (2004), 487–505.

[33] Lynn Dombrowski, Adriana Alvarado Garcia, and Jessica Despard. 2017. Low-wage precarious workers' sociotechnical practices working towards addressing wage theft. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. 4585–4598.

[34] Sandrine Dudoit, Juliet Popper Shaffer, and Jennifer C Boldrick. 2003. Multiple hypothesis testing in microarray experiments. *Statist. Sci.* (2003), 71–103.

[35] Ralph Ellison. 2016. *Invisible man*. Penguin UK.

[36] Frank S Fanselow. 1996. The disinvention of caste among Tamil Muslims. *Caste today* (1996), 202–226.

[37] Damien R Farine. 2017. A guide to null models for animal social network analysis. *Methods in Ecology and Evolution* 8, 10 (2017), 1309–1320.

[38] Raymond Fisman, Daniel Paravisini, and Vikrant Vig. 2017. Cultural proximity and loan outcomes. *American Economic Review* 107, 2 (2017), 457–92.

[39] Linton C Freeman. 1978. Centrality in social networks conceptual clarification. *Social networks* 1, 3 (1978), 215–239.

[40] Linton C Freeman, Douglas Roeder, and Robert R Mulholland. 1979. Centrality in social networks: II. Experimental results. *Social networks* 2, 2 (1979), 119–141.

[41] Kiran Garimella, Gianmarco De Francisci Morales, Aristides Gionis, and Michael Mathioudakis. 2018. Political discourse on social media: Echo chambers, gatekeepers, and the price of bipartisanship. In *Proceedings of the 2018 World Wide Web Conference*. 913–922.

[42] Diego Garlaschelli and Maria I Loffredo. 2004. Patterns of link reciprocity in directed networks. *Physical review letters* 93, 26 (2004), 268701.

[43] Nabeel Gillani, Ann Yuan, Martin Saveski, Soroush Vosoughi, and Deb Roy. 2018. Me, my echo chamber, and I: introspection on social media polarization. In *Proceedings of the 2018 World Wide Web Conference*. 823–831.

[44] Véronique Gille. 2018. Applying for social programs in India: Roles of local politics and caste networks in affirmative action. *Journal of Comparative Economics* 46, 2 (2018), 436–456.

[45] Ishika Gupta, Prakashan Chellattan Veettil, and Stijn Speelman. 2020. Caste, Social Networks and Variety Adoption. *Journal of South Asian Development* 15, 2 (2020), 155–183.

[46] Yasir Hameed. 2016. *Housing Segregation in Delhi: The Role of City Planning*. Ph.D. Dissertation. University of California, Berkeley.

[47] Thomas Blom Hansen. 1993. RSS and the Popularisation of Hindutva.

[48] Itai Himelboim. 2017. Social network analysis (social media). *The international encyclopedia of communication research methods* (2017), 1–15.

[49] Itai Himelboim, Stephen McCreery, and Marc Smith. 2013. Birds of a feather tweet together: Integrating network and content analyses to examine cross-ideology exposure on Twitter. *Journal of computer-mediated communication* 18, 2 (2013), 154–174.

[50] Christophe Jaffrelot. 2015. The Modi-centric BJP 2014 election campaign: New techniques and old tactics. *Contemporary South Asia* 23, 2 (2015), 151–166.

[51] Christophe Jaffrelot. 2019. Class and Caste in the 2019 Indian Election–Why Have So Many Poor Started Voting for Modi? *Studies in Indian Politics* 7, 2 (2019), 149–160.

[52] Christophe Jaffrelot and Gilles Verniers. 2020. The reconfiguration of India's political elite: profiling the 17th Lok Sabha. *Contemporary South Asia* (2020), 1–13.

[53] Craig Jeffrey. 2001. 'A fist is stronger than five fingers': caste and dominance in rural north India. *Transactions of the Institute of British Geographers* 26, 2 (2001), 217–236.

[54] SurinderS Jodhka. 2017. *Caste in contemporary India*. Routledge.

[55] Younbo Jung, Ashley Tay, Terence Hong, Judith Ho, and Yan Hui Goh. 2017. Politician's strategic impression management on Instagram. In *Proceedings of the 50th Hawaii International Conference on System Sciences*.

[56] Andreas Jungherr. 2016. Twitter use in election campaigns: A systematic literature review. *Journal of information technology & politics* 13, 1 (2016), 72–91.

[57] Pragya Kaushika, Please enter your name here, Snehesh Alex Philip , Neelam Pandey , and Aneesha Bedi . 2019. Modi tells MPs: Increase social media following to 3 lakh or ticket may be in jeopardy. https://theprint.in/politics/modi-tells-mps-increase-social-media-following-to-3-lakh-or-ticket-may-be-in-jeopardy/44330/

[58] Eliscia Kinder, Mohammad Hossein Jarrahi, and Will Sutherland. 2019. Gig Platforms, Tensions, Alliances and Ecosystems: An Actor-Network Perspective. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–26.

[59] Haewoon Kwak, Changhyun Lee, Hosung Park, and Sue Moon. 2010. What is Twitter, a social network or a news media?. In *Proceedings of the 19th international conference on World wide web*. 591–600.

[60] Bruno Latour. 2005. Reassembling the social: An introduction to social life.

[61] John Law et al. 1999. Actor network theory and after. (1999).

[62] David Lazer. 2011. Networks in political science: Back to the future. *PS: Political Science and Politics* 44, 1 (2011), 61–68.

[63] Sofus A Macskassy and Matthew Michelson. 2011. Why do people retweet? anti-homophily wins the day!. In *Fifth International AAAI Conference on Weblogs and Social Media*.

[64] Ross Mallick. 1997. Affirmative action and elite formation: an untouchable family history. *Ethnohistory* (1997), 345–374.

[65] Dilip M Menon. 2010. 8 The blindness of insight. *Indian Political Thought* (2010).

[66] Lucia Michelutti. 2004. 'We (Yadavs) are a caste of politicians': Caste and modern politics in a north Indian town. *Contributions to Indian sociology* 38, 1-2 (2004), 43–71.

[67] David Mosse. 2018. Caste and development: Contemporary perspectives on a structure of discrimination and advantage. *World Development* 110 (2018), 422–436.

[68] Kaivan Munshi. 2016. Caste networks in the modern Indian economy. In *Development in India*. Springer, 13–37.

[69] Kaivan Munshi and Mark Rosenzweig. 2006. Traditional institutions meet the modern world: Caste, gender, and schooling choice in a globalizing economy. *American Economic Review* 96, 4 (2006), 1225–1252.

[70] Kaivan Munshi and Mark Rosenzweig. 2013. *Networks, commitment, and competence: caste in Indian local politics*. Technical Report. National Bureau of Economic Research.

[71] Stephen Musembwa and Souren Paul. 2012. Social Networks: Cultural Diversity, Trust, Reciprocity and Social Capital. (2012).

[72] Karine Nahon and Jeff Hemsley. [n.d.]. Democracy. com: A tale of political blogs and content. In *2011 44th Hawaii International Conference on System Sciences*. 1–11.

[73] Udhav Naig. 2019. Major parties confine Dalit candidates to reserved seats. https://www.thehindu.com/elections/lok-sabha-2019/major-parties-confine-dalit-candidates-to-reserved-seats/article26602129.ece

[74] Deepa Narayan. 2002. Bonds and bridges: social capital and poverty. *Social capital and economic development: well-being in developing countries. Northampton, MA: Edward Elgar* (2002), 58–81.

[75] Pervaiz Nazir. 1993. Social structure, ideology and language: caste among Muslims. *Economic and Political Weekly* (1993), 2897–2900.

[76] Oka, Akhil. 2020 (accessed May 31, 2020). Rahul Gandhi Posts Wrong Indian Map; Deletes Tweet After BJP Highlights Discrepancy. https://www.republicworld.com/india-news/politics/rahul-gandhi-deletes-contentious-tweet.html.

[77] Aditya Pal and Scott Counts. 2011. Identifying topical authorities in microblogs. In *Proceedings of the fourth ACM international conference on Web search and data mining*. 45–54.

[78] Joyojeet Pal and Andre Gonawela. 2016. Political social media in the global South. In *Conference on e-Business, e-Services and e-Society*. Springer, 587–593.

[79] Suhas Palshikar, Sanjay Kumar, and Sanjay Lodha. 2017. *Electoral Politics in India: The Resurgence of the Bharatiya Janata Party*. Taylor & Francis.

[80] Anmol Panda, A'ndre Gonawela, Sreangsu Acharyya, Dibyendu Mishra, Mugdha Mohapatra, Ramgopal Chandrasekaran, and Joyojeet Pal. 2020. NivaDuck - A Scalable Pipeline to Build a Database of Political Twitter Handles for India and the United States. In *Proceedings of the 11th International Conference on Social Media and Society* (Chicago, IL, USA) *(SMSociety '20)*. Association for Computing Machinery, New York, NY, USA, 15.

[81] Anmol Panda, Ramaravind Kommiya Mothilal, Monojit Choudhury, Kalika Bali, and Joyojeet Pal. 2020. Topical Focus of Political Campaigns and its Impact: Findings from Politicians' Hashtag Use during the 2019 Indian Elections. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW1 (2020), 1–14.

[82] TS Papola. 2014. Economic diversification and labour market dynamics in rural India. *Indian Journal of Agricultural Marketing* 28, 3 (2014), 18–33.

[83] John W Patty and Elizabeth Maggie Penn. 2017. Network theory and political science. In *The Oxford handbook of political networks*. Oxford University Press, 147.

[84] J PHULE. 1873. 1991)"Gulamgiri–Slavery". *Collected Works of Mahatma Phule* (1873).

[85] Oliver Posegga and Andreas Jungherr. 2019. Characterizing Political Talk on Twitter: A Comparison Between Public Agenda, Media Agendas, and the Twitter Agenda with Regard to Topics and Dynamics. In *Proceedings of the 52nd Hawaii International Conference on System Sciences*.

[86] Ashwin Rajadesingan, Anmol Panda, and Joyojeet Pal. 2020. Leader or Party? Personalization in Twitter Political Campaigns during the 2019 Indian Elections. In *International Conference on Social Media and Society*. 174–183.

[87] Shakuntala Rao. 2018. Making of selfie nationalism: Narendra Modi, the paradigm shift to social media governance, and crisis of democracy. *Journal of Communication Inquiry* 42, 2 (2018), 166–183.

[88] Fabián Riquelme and Pablo González-Cantergiani. 2016. Measuring user influence on Twitter: A survey. *Information processing & management* 52, 5 (2016), 949–975.

[89] Daniel M Romero, Wojciech Galuba, Sitaram Asur, and Bernardo A Huberman. 2011. Influence and passivity in social media. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*. Springer, 18–33.

[90] Lloyd I Rudolph and Susanne Hoeber Rudolph. 1984. *The modernity of tradition: Political development in India*. University of Chicago Press.

[91] Akrati Saxena, Jaspal Singh Saini, Yayati Gupta, Aishwarya Parasuram, SRS Iyengar, et al. 2015. Social network analysis of the caste-based reservation system in india. *arXiv preprint arXiv:1512.03184* (2015).

[92] Joseph Seering, Felicia Ng, Zheng Yao, and Geoff Kaufman. 2018. Applications of Social Identity Theory to Research and Design in Computer-Supported Cooperative Work. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (2018), 1–34.

[93] Ronojoy Sen. 2016. Narendra Modi's makeover and the politics of symbolism. *Journal of Asian Public Policy* 9, 2 (2016), 98–111.

[94] Express News Service. 2020 (accessed May 31, 2020). Tamil Nadu BJP deletes tweet on Periyar after facing backlash from political parties. https://www.newindianexpress.com/states/tamil-nadu/2019/dec/25/tamil-nadu-bjp-deletes-tweet-on-periyar-after-facing-backlash-from-political-parties-2080601.html.

[95] Ghanshyam Shah. 2004. *Caste and democratic politics in India*. Orient Blackswan.

[96] Ghanshyam Shah. 2015. Mega Marketing and Management: Gujarat's 2014 Elections. *India's 2014 Elections: A Modi-led BJP Sweep* (2015), 258.

[97] Ghanshyam Shah, Harsh Mander, Sukhadeo Thorat, Amita Baviskar, and Satish Deshpande. 2006. *Untouchability in rural India*. Sage.

[98] John Shiga. 2007. Translations: artifacts from an Actor-Network perspective. *Artifact: Journal of Design Practice* 1, 1 (2007), 40–55.

[99] Sean L Simpson, Robert G Lyday, Satoru Hayasaka, Anthony P Marsh, and Paul J Laurienti. 2013. A permutation testing framework to compare groups of brain networks. *Frontiers in computational neuroscience* 7 (2013), 171.

[100] Mohinder Singh and Rajarshi Dasgupta. 2019. Exceptionalising democratic dissent: a study of the JNU event and its representations. *Postcolonial Studies* 22, 1 (2019), 59–78.

[101] Shamsher Singh et al. 2015. Residential Segregation and Access to Basic Amenities: A Village-Level Case Study. *Journal, Review of Agrarian Studies* 5, 2 (2015), 126–46.

[102] LIA SPINPER. 2020. The SPINPER Project – The Social Profile of the Indian National and Provincial Elected Representatives (to appear). http://liaspinper.com.

[103] Tiziano Squartini, Francesco Picciolo, Franco Ruzzenenti, and Diego Garlaschelli. 2013. Reciprocity of weighted networks. *Scientific reports* 3, 1 (2013), 1–9.

[104] MN Srinivas and André Béteille. 1964. 212. Networks in Indian Social Structure. *Man* 64 (1964), 165–168.

[105] Scroll Staff. 2020 (accessed May 31, 2020). BJP MP Tejasvi Surya's old tweet on Arab women sparks backlash, Indian envoy appeals for restraint. https://scroll.in/latest/959836/bjp-mp-tejasvi-suryas-old-tweet-on-arab-women-sparks-backlash-indian-envoy-appeals-for-restraint.html.

[106] Business Standard. 2020 (accessed May 31, 2020). Year in Review: 10 events that changed India's political discourse in 2019. https://www.business-standard.com/article/current-affairs/year-in-review-10-events-that-changed-india-s-political-discourse-in-2019-119122701252_1.html.

[107] Stefan Stieglitz and Linh Dang-Xuan. 2012. Political communication and influence through microblogging–An empirical analysis of sentiment in Twitter messages and retweet behavior. In *2012 45th Hawaii International Conference on System Sciences*. IEEE, 3500–3509.

[108] Anagha Tambe. 2019. (Hyper) Visible 'Women'/Invisible (Dalit) Women: Challenging the Elusive Sexism in Indian Universities. In *Strategies for resisting sexism in the academy*. Springer, 129–149.

[109] The Telegraph. 2019. Study finds SC and ST journalists missing from Indian media. https://www.telegraphindia.com/india/study-finds-sc-and-st-journalists-missing-from-indian-news-media/cid/1695824

[110] Joseph Tharamangalam. 1996. Caste among christians in India. *Caste: Its Twentieth Century Avatar,(ed.) MN Srinivas, Viking, New Delhi* (1996), 263–291.

[111] Sukhadeo Thorat and Paul Attewell. 2007. The legacy of social exclusion: A correspondence study of job discrimination in India. *Economic and political weekly* (2007), 4141–4145.

[112] Sukhadeo Thorat and S Madheswaran. 2018. Graded Caste Inequality and Poverty: Evidence on Role of Economic Discrimination. *Journal of Social Inclusion Studies* 4, 1 (2018), 3–29.

[113] Carol Upadhya. 2007. Employment, exclusion and'merit'in the Indian IT industry. *Economic and Political weekly* (2007), 1863–1868.

[114] Palashi Vaghela, Ramaravind K Mothilal, and Joyojeet Pal. 2021. Birds of a Caste? How Caste Hierarchies Manifest in Retweet Behavior of Indian Politicians. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW3 (2021), 1–24.

[115] Milan Vaishnav. 2019. The BJP in Power: Indian Democracy and Religious Nationalism.

[116] Ananya Vajpeyi. 2020. Minorities and Populism in Modi's India: The Mirror Effect. In *Minorities and Populism–Critical Perspectives from South Asia and Europe*. Springer, 17–28.

[117] Reeve Vanneman, James Noon, Mitali Sen, Sonalde Desai, and Abusaleh Shariff. 2006. Social networks in India: Caste, tribe, and religious variations. In *Proceedings of the Annual Meeting of the Population Association of America*. University of Maryland College Park.

[118] Subodh Varma. 2012. SC/STs fail to break caste ceiling: No SC in 149 top government officers, 40 pc do menial jobs. https://economictimes.indiatimes.com/news/politics-and-nation/sc/sts-fail-to-break-caste-ceiling-no-sc-in-149-top-government-officers-40-pc-do-menial-jobs/articleshow/16278743.cms

[119] Gilles Verniers. 2019. The Return of Thakurvad. https://www.indiatoday.in/magazine/cover-story/story/20190429-the-return-of-thakurvad-1504672-2019-04-19

[120] Gilles Verniers and Christophe Jaffrelot. 2019. Explained: Why so many MPs are dynasts. *The Indian Express* 27 (2019).

[121] M Vijayabaskar and A Kalaiyarasan. 2014. Caste as Social Capital: The Tiruppur Story. *Economic and Political Weekly* (2014), 34–38.

[122] Balagopal Vissa. 2011. A matching theory of entrepreneurs' tie formation intentions and initiation of economic exchange. *Academy of Management Journal* 54, 1 (2011), 137–158.

[123] Trina Vithayathil. 2018. Counting caste: Censuses, politics, and castelessness in india. *Politics & Society* 46, 4 (2018), 455–484.

[124] Michael D Ward, Katherine Stovel, and Audrey Sacks. 2011. Network analysis and political science. *Annual Review of Political Science* 14 (2011), 245–264.

[125] Stanley Wasserman, Katherine Faust, et al. 1994. *Social network analysis: Methods and applications*. Vol. 8. Cambridge university press.

[126] Bob Wheeler and Marco Torchiano. 2016. *lmPerm: Permutation Tests for Linear Models*. https://CRAN.R-project.org/package=lmPerm R package version 2.1.0.

[127] Chi-Lan Yang, Chien Wen Yuan, and Hao-Chuan Wang. 2019. When Knowledge Network is Social Network: Understanding Collaborative Knowledge Transfer in Workplace. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–23.

A APPENDIX

PageRank centrality gives us a sense of how influence in an information network like Twitter can be compounded based on the number of followers a node has, the extent to which they are parsimonious towards following other members of the network, and how many important people they are following. Thinking about this from a caste perspective, it helps us interpret how influence and the importance of nodes from a particular caste shapes the way the user get retweeted within the network (for example.) The relationship between PageRank centrality and social capital is positive owing to the fact that being connected to more important or well-connected nodes translates into more influence in a network. [14, 16]. Indeed, PageRank based algorithms have been widely used in social media to identify influential users [89], rank users by their ability to gain and broadcast information[59], and to discover authorities within specific topics [77].

Another measure of centrality commonly used in network science is **betweenness centrality**[88]. Actors with high betweenness create short connections between other actors, creating opportunities for exploitation of information and control benefits. While there is typically a correlation between PageRank and betweenness, the latter captures a different type of structural advantage. Betweenness measures the bridging ability of a node in a network. In our context, the greater the value of betweenness for an MP, the more people in the network depend on them to make connections with other MPs [16, 39]. Comparing the betweenness of different castes could illuminate the extent of disruption that can be caused by removing MPs of particular castes in the communication between different parts of the network.

This is of particular interest from a caste perspective because it helps us interpret what kind of bridging capital MPs from different castes serve as - that is, are they relying on outgoing connections more for bridging capital or incoming connections?

In the spirit of wanting to understand caste relations and their nature on Twitter, the question of **reciprocity** becomes important. It determines the nature of relationships in a network such that we know if it is a mutual exchange of information or not. Previous work on reciprocity as a network measure has shown that it can also be a measure of mutual trust and status similarity between two individuals or meso-groups [24, 59]. Thus of keen interest on Twitter follower and friends networks, which is directed in nature, is the question of how does the communication between two users take place only in one direction, or is it reciprocated?

Particularly in the case of caste in India, untouchability and casteist attitudes continue to perniciously manifest in everyday life for lower castes. While elite lower castes are a minority in India, those who are educated, mobile, and urban try to move away from the identity of their community to climb the social ladder more easily [90] Yet in some cases, members of lower castes who want to cut adrift from traditional moorings are not able to forge links with other groups in a satisfactory manner. This is where the role of reciprocity or mutual connections becomes central in analyzing caste as social capital. Studies of inter-caste friendships between co-located Indians have shown that exposure to neighbors of other castes, and thus their world, culture, and perspective, increases inter-caste trust and the belief that caste injustice is growing[13].

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