Probing Patterns of Informal Ties in Patronage Networks: A Social Network Analysis Approach

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***Abstract*—Informal networking plays a crucial role in developing patronage coalitions in many sectors across countries. Among Chinese politicians, patronage networks formed between colleagues or between promotees and promoters affect their career prospects profoundly. The continued incompleteness of publicly available data limits our ability to quantitatively characterize patronage networks. While previous studies have applied network analysis on few existing datasets about Chinese politicians, most of them did not employ advanced techniques for this approach. In this paper, we provide a preliminary analysis for patronage networks of politicians in China using advanced network analysis tools. We are able to characterize the patronage networks with methods including community detection and network motifs. Furthermore, after mapping nodes to low dimensional feature vectors based on network structures, we show that the possibilities of committing to a crime and the levels of positions in the system are associated with network patterns of the politicians.**

***Index Terms*—data mining, social network analysis, political science, patronage network**

I. Introduction

The tendency of people connecting with each other can be dated back to the co-residence pattern in the group structure of hunter-gatherers [1]. This pattern refers to the phenomenon that our ancestors tend to reside together and form social groups. Nowadays, people connect in more diverse ways, including forming professional networks between colleagues [2]–[4], social networks between families and friends [5]–[8], as well as local communities between those who share hobbies [9].

Informal connections formed in networks have an impact on people's life in various aspects. In propaganda campaigns, advertisement is altered depending on the user's position in the communities of networks [10]. Additionally, social platforms such as Facebook benefit people who reported experiencing low self-esteem and life satisfaction through connecting them in a virtual community [11]. Outside social networks, numerous studies on social capital have shown the influence of informal ties on one's possibility of being successful in professional settings [12]–[14]. Books that serve as guides for career planning rarely give advice without mentioning the importance of networking [15].

In modern Chinese politics, informal connection, known as *Guanxi*, plays an particularly important role in the career of politicians [16]–[21]. With the traditionally rooted aversion to institutionalized bureaucracy, Chinese politicians have a tendency to form moralistic and informal connections between colleagues [22]. For instance, the possibility of a candidate getting promoted is influenced by the share of the candidates' hometown with *high-ups* [23]. Additionally, informal connections can often help politicians to work around formal constraints [24].

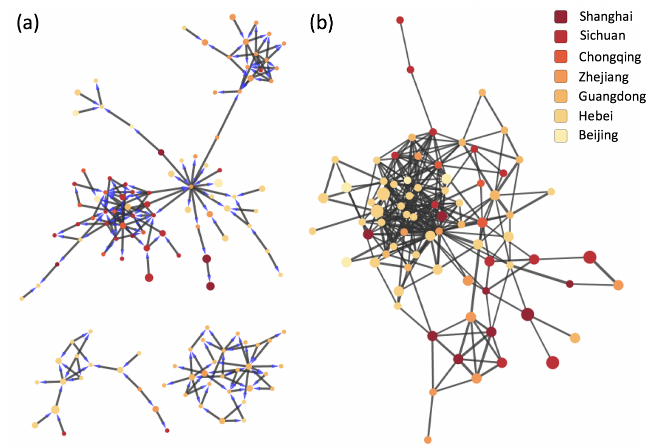

Fig. 1. Visualizations of subgraphs of the professional network and the patron-client network. The nodes are colored based on their home provinces. The size of the nodes are proportional to their levels of last positions. (a) In patron-client network, promoters and promotees are connected with directed edges. We have 3 disconnected components in the subgraph. The edge is pointing from politcians to their promoters, whose directions are indicated as arrows in blue. (b) In the professional network, edges are connected between colleagues. The weights of edges represent how long two politicians have worked together.

Ties, or edges, in networks can be formed for different reasons. Among hunter-gatherers, groups are usually formed by brothers and sisters [1]. In online social networks, connections are often built based on shared common experiences or habits [5], [9]. In professional networks, bonds can be made between colleagues or between managers and employees [15]. Besides shared work experiences, informal ties between politicians can be formed by patron-client relations in Southeast Asia. The centered politicians in the network will serve as leaderships who provide protections and promotions for their followers [25]. As a result, the patron-client relation explains one of the reasons why politicians are highly factional affiliated in Southeast Asia.

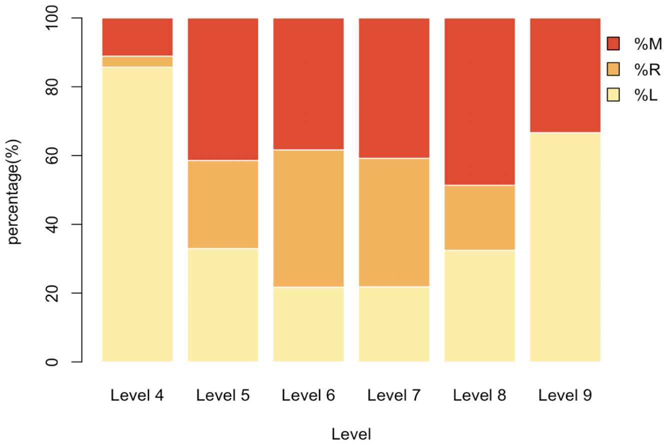

Fig. 2. Community (faction) distributions for politicians from level 4 to 9 in the patron-client network. M refers to the politicians who reside in the overlapped community between community L and R.

In this study, we built networks based on a publicly available biographical database that contains biographical information and work histories of more than 4000 politicians in China ranging from 1990s to 2015. The database also contains indications of whether a politician has involved in a corruption crime. To examine the patterns in the networks formed by informal connections between politicians in China, we first constructed two networks: a professional network where people are connected through work, and a patron-client network where politicians and their promoters are tied in the political system (Fig. 1).

Clusters And Factions Detection We studied how sharing a hometown will affect the possibility of becoming colleagues within the professional network. We found that politicians from Chongqing were clustered together, and often work together in the network. Additionally, we studied factions of the politicians within the patron-client network. By applying community detection algorithms on the patron-client networks, our results suggest that the members in the central committee of CCP - Chinas Politburo, belong to one unified faction as there is no bifurcation of politics such as left and right wings. This is consistent with the concept of a single ideology by the constitution of China [26], as the Chinese Communist Party (CCP) is often considered as one unified system. However, we found that the mid-level politicians are often factional affiliated.

Career Predictions And Powering Structure By using the patterns of ties in our patron-client network, we found that the node level features, embedded using *node2vec*, were associated with the career path of politicians and their biographical information. Using the node feature vectors in the patron-client network formed from 1990s to 2005, we were able to predict the levels of last positions and corruption involvements after 2005 for all politicians. Besides, we showed that node features could be used to predict gender and education level.

In addition to node level patterns, we explored network patterns in a large scope. Motif refers to a simple building block of a complex network. The motif distributions were used to study the interplays between nodes in networks in biology [27], [28], chemistry [29] and social science [30]–[32]. We counted the occurrences of different transformations of motifs to understand the power structure underlying the patron-client network in CCP. Specifically, by applying motif analysis to this network, we found that individuals who are promoted by the same persons have a tendency to promote each other as well.

In this paper, we presented the first study that examined networks formed by Chinese politicians by applying advanced network analysis techniques including community detection, motif analysis and node label predictions. We are able to make meaningful inferences from the networks using such methods. When government transparency is lacking, this social network analysis approach provides value for researchers who aim to better understand politics in China and other countries as well.

II. Related Work

Network analysis has been used in various fields of research, such as biology [33]–[36], social network [5]–[8], linguistics [34], [37], [38], recommendation services [39]–[41], disease control [42]–[44], psychology [45], [46] and political science [47], [48]. The areas of interests in these studies can be classified into two main categories - network pattern recognition and learning. Network pattern recognition is associated with the use of algorithms corresponding to community and role detection [49]–[51], motif analysis [32], [52], [53], graph representation learning [54]–[56] and network cascade [57]–[59]. For example, using community and role detection techniques, analysis on cosponsorship networks identifies the relationship between cosponsors of legislation and their sponsors and predicts legislative influence from the proposed legislation in the U.S. House and Senate. [47]. In another study on U.S. politics, the researchers were able to quantify the level of cooperation between members of opposite parties in the U.S House Representatives legislative decisions by using cluster analysis [48]. The other focus - learning includes methods for link and label prediction [60]–[62] and graphical deep learning [63], [64]. For instance, previous study successfully used supervised learning with network features to predict links in authorship networks [65]. Additionally, researchers in biology, by leveraging methods for link and label prediction, were able to predict associations between proteins and diseases [66].

There exists numerous studies using quantitative methods on different aspects of occupational mobility in China including promotion [67]–[69], demotion [19], [70] and transition [71]. For example, researchers demonstrated a causal relationship between the probability of getting promoted and work performance and patronage in Chinese politicians [71]. Additionally, having informal connections with high-ups has been shown to influence the chance of a politician getting promoted [23]. Inspired by previous research, our study aims to uncover the

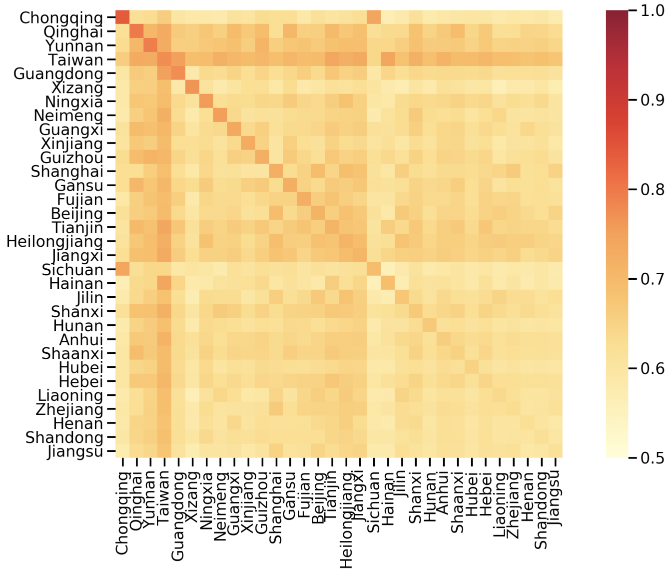

Fig. 3. The heatmap of similarity scores for every pair of provinces across 32 provinces. The similarity scores for politicians range from $[0.5, 1]$. Darker color represents higher similarities corresponding to clustered groups.

patterns and influence of informal ties formed by Chinese politicians using network analysis.

In recent years, the ideas of using network-based approach has received increasing attention in research community of political science. The researchers often construct networks with work relations between politicians [72]–[76]. For example, Keller demonstrated that by network-based approach, researchers were able to visualize and analyze relations between factions among Chinese elite politicians [77]. However, few of them have a special focus on patterns of the network connections between politicians. Of such studies, basic network characteristics and elite politicians are often the targets in analysis [74], [77]–[79]. More advanced network analysis tools including motif analysis, role and community detection and graph representations are lacking. In our study, we utilize advanced network analyses in studying patronage patterns in politics of China, and inferring political meanings from these network connections.

III. Networks

To construct networks, we used Chinese Political Elite Database (CPED)[1], a large biographical database that contains extensive demographic and career information of 4,057 political leaders from various levels of positions, ranging from grassroots (Level 4 and below) to national levels (Level 8 and above) in China since 1990s [80]. For these leaders, the database provides information regarding time, place, organization, and rank of every job assignment listed in their resumes. Such data is collected from government websites, yearbooks, and other reliable Internet sources. For the rest of the paper, we made our analyses anonymous without exposing the names of politicians. Levels of politicians range from level 1 to level 9. We refer politicians with level 4 and below as grassroots officials, level 6 to level 7 as middle level officials, and level 8 and above as top level officials.

[1]http://www.junyanjiang.com/uploads/5/8/1/9/58193547/cped_v1.0.rar

A. Professional Network

Our professional network (Fig. 1b) is constructed based on overlapped work experiences of all political leaders. Each node in the network represents a unique politician. Two nodes are connected with an undirected edge if the politicians were colleagues. Edge is weighted by the length of time of them working together.

B. Patron-client Network

Our patron-client network (Fig. 1a) is constructed by patron-client relations of the political leaders. Each node in the network represents a unique politician. Nodes are connected with directed edges going from the politicians towards their promoters.

IV. Analysis

A. Community Detection in Patron-client Network

To examine factions in CCP, we applied community detection algorithm to the patron-client network that describes the patronage relations between politicians. We used *BIGCLAM*, an overlapping community detection method that scales to large network, to detect communities [81]. Before applying *BIGCLAM* to this network, we first removed the directions in edges as we were only interested in undirected patronage relations. Given an unlabeled undirected network $G(V, E)$ with N nodes, the algorithm tries to detect K communities by maximizing the likelihood $l(F) = \log P(G|F)$, where F is the likely affiliation factor $F \in \mathbb{R}^{N,K}$. Formally, we tried to find the optimized $\hat{F}$ with $F \geq 0$:

$$\hat{F} = \text{argmax } l(F) \tag{1}$$

where

$$l(F) = \sum_{(u,v)\in E} \log(1 - \exp(-F_u F_v^T)) - \sum_{(u,v)\notin E} F_u F_v^T \tag{2}$$

Given K, we learned $\hat{F}$ that best estimated the adjacency matrix A of our graph G. Finally, we assigned nodes to communities using the estimated $\hat{F}$ which contained probabilities of nodes corresponding to different communities. Nodes that had same probabilities for different communities were assigned to both communities.

B. Community Detection with Hometown

Using the professional network, we studied the clustering patterns based on hometowns. Specifically, we looked at the probabilities of working together for politicians between any two provinces. First, we embedded all nodes into 128-dimensional vectors using $node2vec$ [54] with tuned parameters. Formally, having just traversed the edge from node x to

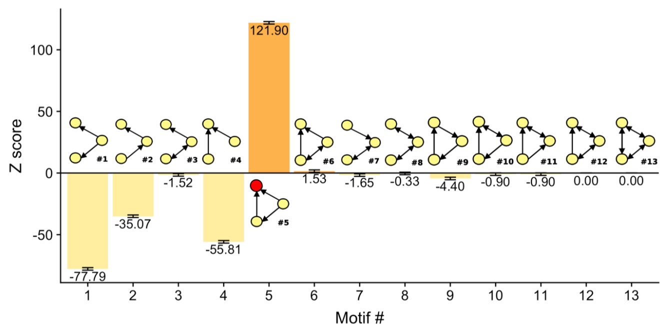

Fig. 4. The network significance profile of the patron-client network. Bars represent the normalized z scores for different motif transformations. Motifs are overlaid on the plot. Higher z score means more frequent occurrences in the network. For motif #5, the promoter is colored as red.

node y, the unnormalized transition probability of traversing from node y to a neighboring node z is given by:

$$\alpha_{pq}(x,z) = \begin{cases} 1, & \text{if } d_{xz} = 0 \\ 1, & \text{if } d_{xz} = 1 \\ 2, & \text{if } d_{xz} = 2 \end{cases} \tag{3}$$

where d_{xz} represents the distance in hops between node x and node z. Setting higher probabilities with larger d_{xz} will embed nodes that are clustered together with similar vectors [54]. Subsequently, we calculated cosine similarity scores between vectors of politicians A and B from different provinces in China, which range from $[-1, 1]$:

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}} \tag{4}$$

Finally, we calculated averaged similarity scores for every pair of 32 provinces and produced a heatmap (Fig. 3). Politicians from different provinces have a high similarity score if they are clustered together in the professional network.

C. Motif Distributions

Motifs are the building blocks of a complex network. Here, we quantified the distribution of different non-isomorphoic transformations of motifs of size 3 for the patron-client network. To count the motifs, we adapted *ESU* algorithm [82]. To produce the network significance profile, we compared the distribution of motifs of our patron-client network with a configuration model. This model was randomly generated by holding constant the counts of nodes and edges, and the degree distribution [83]. We assigned a score Z_i for every transformation of motifs of size 3:

$$Z_i = \frac{(N_i^{\text{patron-client}} - N_i^{\text{configuration}})}{\text{std}(N_i^{\text{configuration}})} \tag{5}$$

Following this, we plot the distribution of the scores for 13 different transformations.

D. Associations between Career Path and Node Features

In this analysis, we want to find if network patterns are associated with career path of a politician. Specifically, we used a linear regressions to fit a model using node level features from a patron-client network constructed with data before 2005 to predict a binary value indicating whether a politician committed to a corruption crime, and the final levels of the politician after 2005. Additionally, we used node level features to predict education levels and genders. First, we reconfigured the patron-client network by using the data only from 1990s to 2005. In parallel with the community detection procedure we employed earlier, we embedded our nodes into vectors using *node2vec* with the following unnormalized transition probabilities which are tuned to discover structurally similar nodes:

$$\alpha_{pq}(x,z) = \begin{cases} 2, & \text{if } d_{xz} = 0 \\ 1, & \text{if } d_{xz} = 1 \\ 1, & \text{if } d_{xz} = 2 \end{cases} \tag{6}$$

As a result of setting higher probabilities with smaller d_{xz}, nodes that are structurally alike will be embedded with similar vectors [54]. Then, we used the fit regression models with embedded vectors and actual values corresponding to predictions of career path of politicians after 2005 along with education levels and genders. For binary and multi-class classifications, we used logistic regression and linear regression respectively. To illustrate predictive powers of network features, we looked for existences of significant differences in fitted values for different groups.

V. Results

A. Distributions of Factions

Informed by the results from the overlapped community detection algorithm *BIGCLAM*, we classified all nodes into three mutually exclusive communities: community L, R and M. Specifically, this algorithm first assigned nodes to two communities L and R with overlaps. Then, we reassigned nodes that were in the overlapped community with a new community M. Here, the names of the communities were arbitrarily chosen as they did not indicate actual political ideologies.

Although the communities did not map to actual political ideologies, we found that the representations of the communities depended on the levels of politicians (Fig. 2). Particularly, among the politicians of level 9 who were the top leaders and politicians of level 4 who were the grassroots officials, most politicians were assigned to either community L or the overlapped community M. However, we found separations between communities for the mid-level politicians whose levels ranged from 5 to 8. Surprisingly, this result contradicts with what previous studies on factions among Chinese elite politicians where researchers demonstrated that top political leaders in China are factional affiliated [84]. In addition, previous literature on reforming Chinese political system to

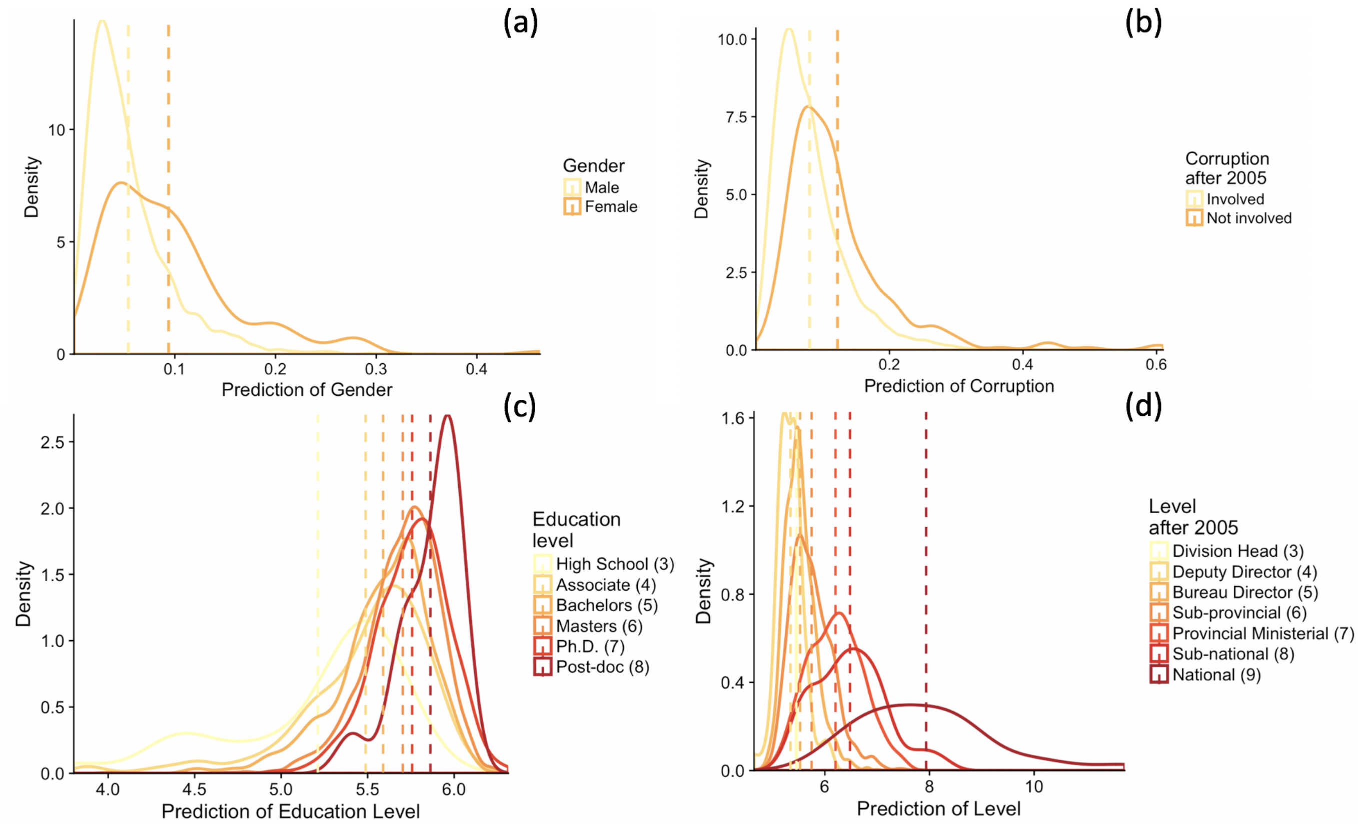

Fig. 5. The predicted values based on network features group by true values for genders, involvements of corruption, levels of educations and levels of final positions. (a) The distributions of predicted genders for all politicians grouped by their actual genders. 0 and 1 map to male and female respectively. (b) The distributions of predicted involvements in corruptions after 2005 based on the network features before 2005 grouped by actual involvements in corruptions. 0 and 1 map to someone not involved in corruption and someone did. (c) The distributions of predicted levels of education for all politicians grouped by their actual levels of education. The levels of educations are listed in the plot with corresponding values. (d) The distributions of predicted levels of final positions for all politicians after 2005 by using network features before 2005. The levels of positions are listed in the plot with corresponding values.

reduce factionalism mainly focused on top-level or buttom-up politicians, whereas mid-level politicians rarely received attention [85]. However, these results suggest that top leaders and grassroots officials are actually unified as one community whereas mid-level politicians are more factional affiliated.

B. Hometown Matters

To visualize the effect of shared hometowns on clustering, we plotted a heatmap of similarity scores for every pair of provinces across 32 provinces. The heatmap was symmetric with respect to the diagonal axis. In the heatmap, the similarity scores quantified the degree to which politicians from two provinces clustered together in the professional network, which further characterizes their closeness of work relationship. In our case, all of the similarity scores ranged from $[0.5, 1]$.

In the diagonal axis (Fig. 3), the scores represent whether politicians from the same provinces were clustered together in the professional network. In most cases, our results suggest that sharing a home province influenced the chance of the politicians clustering together in the network. This is especially relevant to politicians from Chongqing who clustered together and had a tendency of becoming colleagues. We also found that those who are from Sichuan and Chongqing preferred to work together. This is not surprising given the fact that Sichuan and Chongqing are located in close proximity. This finding is consistent with previous studies on quantifying the relations between informal ties and relational demography among Chinese politicians [86], [87]. In these studies, researchers demonstrated that demographic similarities such as sharing hometowns plays an important role in forming connections among Chinese politicians. On the other hand, politicians from Taiwan evidently stood out with a unique pattern in the heatmap. They were almost equally clustered with politicians from all provinces. This distinct pattern has been reported in previous quantitative research which showed that the influence of demographic similarities on work relations is different for Taiwan [86]. Taken together, our results demonstrate that home origins are associated with differential patterns of how politicians are clustered in the professional network.

C. Uncovering the Patronage Mechanism

We plotted the normalized z scores for each motif transformation in the patron-client network (Fig. 4). Based on the scores, we found that motifs that have bidirectional edges were often associated with low z scores, which means that bidirectional edges are rarely present in the network. This suggests that the promotees rarely exceed the levels of their promoters. On the other hand, the z score for motif $\#5$ is significantly higher than others. We highlighted the promoter in motif $\#5$ with red color given the fact that all the edges are pointing from the promotees towards the promoters in the patron-client network. Comparing to motif $\#4$, motif $\#5$ has an additional edge residing between two promotees. In other words, our results suggest that the politicians promoted by the same promoter tend to promote each other. This is consistent with previous studies in patron-client networks of Chinese politicians which demonstrated that all the followers of one shared central leaders form a clique and protect each other in the group [25].

D. You Are Who You Surround Yourself with

To illustrate the predictive power of network features, we plotted the density distributions of predicted values grouped by the true values for each prediction task compensating with predictions of gender, corruption involvement, level of education and level of last position after 2005 (Fig. 5). As presented in the plots, these distributions are biased because the sample sizes for different groups in each task are unbalanced. For example, in the gender plot where male was labeled as 0 and female as 1, the prediction values for female politicians were biased towards 0 as we had fewer female politicians in our patronage networks. Similarly, in the corruption involvement plot, we labeled politicians 1 if involved in corruption and 0 otherwise. Because we have fewer corrupted politicians in the network, the distributions are biased towards 0. However, as indicated by the dashed line that represents the mean of each group, the differences between each group are significant. For instance, the mean predicted values of the corrupted politicians are significantly lower ($t = -8.1126, p < 0.005$) compared to that of uncorrupted politicians. In parallel, we showed that the predicted levels for last positions are distributed distinctively for each group. For example, we found significant differences in the distribution between level 9 and level 8 ($t = -5.3679, p < 0.005$), level 8 and level 7 ($t = -3.7015, p < 0.005$), and level 7 and level 6 ($t = 17.122, p < 0.005$). Taken together, we demonstrated that node level features based on the patterns of ties in the patron-client network were associated with real life outcomes, including gender, involvement in corruption, education level and final level in the career. More importantly, we showed that the levels of final positions of politicians are associated with the patronage connection patterns they formed in their earlier stages of careers, which in this case refers to years before 2005.

VI. Conclusion

In this paper, we aimed to probe the politics of China using advanced network analysis tools in two ways. First, we analyzed patterns of informal ties formed by Chinese politicians by constructing two networks on the publicly available database CPED, including the professional and patron-client networks. Specifically, we examined degree of factions across different levels of politicians, the effect of shared hometown on clustering, and the power structure of patron-client network. An in-depth analysis of community detection in the patron-client network showed that top-level leaders and grassroots officials in CCP were not factional affiliated, unlike mid-level politicians. In addition, our results of community detection analysis on the professional network suggest that the likelihood of the politicians being colleagues is associated with their home provinces. Finally, to uncover the patterns for the power structure, further analysis on the patron-client network showed that politicians who shared a common promoter preferred to promote each other as well.

Besides exploring the patterns of network connections mentioned above, we successfully show the predictive power of patron-client network patterns by illustrating the associations between the network features and one's career path. This includes politicians' engagement in corruption and levels of final positions. Furthermore, we demonstrated the network pattern were also associated with biographical information including gender and levels of education.

The results of our study indicate that top leaders and grassroots officials are not factional affiliated in the way previous studies suggested. However, without mapping to actual political ideologies or categories, our results might overlook the underlying mechanisms of the factional affiliations which could be useful for explaining the clustering structure of politicians. In future research, we will use the factional patterns discovered in the current study and aim to interpret the results based on actual political ideologies of politicians. Furthermore, while the network features are associated with career path and biographical information, causal meanings for such analyses are lacking. In future study, we can control confounding factors and analyze the treatment effects of different network features to understand the causal relations between network patterns and career path.

To conclude, by using the publicly available records of more than 4,000 politicians from China, we were able to detect the patterns of informal ties which were echoed in literature of political science, and used the patterns to predict career path and biographical information. By applying advanced network analysis tools to this database, we provided a way to better understand and quantify the underlying patronage mechanisms by using China as our example. We therefore believe that the pattern detection introduced in the paper backed by network analysis can be adapted to study the politics of other countries as well.

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