# Networks and Promotion inside Large Bureaucratic Systems

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**Abstract**

This project investigates networks and promotion inside a large bureaucracy using multiple approaches from network analysis. We hypothesize that network characteristics, such as sponsorship relations, community homogeneity and workplace affiliations, have significant impact on one's promotion prospect. Using PageRank and community detection algorithms and a discrete-time Markov chain for modeling job transitions, we have found conclusive evidence that networks matter more than conventional non-network aspects, such as job performance, to bureaucratic career advancement.

## I. Introduction

This project investigates the network patterns inside a large bureaucratic system. Modern bureaucracy permeates social and political spheres as an important form of organizing hierarchies, coordinating resources and activities. To this date, however, most of the bureaucratic systems remain a black box, as little is known about their internal personnel flow pattern, as well as the connections among individuals and organizations. It is yet an important task to examine the personnel flow and network patterns inside bureaucratic agencies, as doing so will shed new light on how the bureaucracy functions in controlling resources and coordinating activities.

The main purpose of the current study is three-fold: 1) we would like to investigate the network connections among individuals inside a bureaucracy and examine the importance of networks on bureaucratic career mobility. Specifically, how important are networks to promotion compared to non-network aspects, such as job performance? A related issue is on the network pattern and community structure of individuals in bureaucracies. 2) How do networks and communities evolve over time inside bureaucratic systems, and what kind of community structures facilitates individual mobility? In addition, individual mobility across organizations provides inferences on the connections among bureaucratic agencies. 3) How are bureaucratic organizations connected to each other based on individual mobility, and what kinds of organizations provide better mobility chances? Using multiple algorithms and methods in network analysis, we pursue the three issues above in analyzing the network structures inside a large bureaucratic system.

## II. Literature Review

The importance of social networks to organizational careers has been a long-standing topic in social sciences research and network analysis. The early theories on the "strength of weak ties" and "structural holes" point out the surprising effect of long-range edges in networks that transmit otherwise unavailable information and opportunities in distant social components (Burt 1990; Granovetter 1995). In research on political organizations and bureaucracies, however, the discussion of social networks often takes on a different theme. Instead of the "strength of weak ties," researchers speculate on the importance of factionalist closure, sponsorship and political loyalty in bureaucratic careers. Various ethnographic studies provide anecdotal evidence on the factionalist and cliquish connections among local bureaucrats and politicians, and how a bureaucrat's career is transformed by his contact with a high-status political elite. On the other hand, competing hypothesis emphasizes the impact of other more tangible career aspects on job mobility, such as performance and qualifications, following the tradition of Max Weber in characterizing bureaucracy as rationalized and efficient machinery based on career specialization, formal rules, and selectivity on expertise and performance. Such a characterization of formal organizations implicitly assumes that the "informal factors" of network connections are ignored in job evaluations and promotion decisions.

The performance-based hypothesis on job mobility inside organizations has gained popularity, especially in the "tournament model" in personnel economics, which describes career advancement as a yard-stick competition based on individual performance at each stage of one's career. Only the winner of a competition, however, could get the opportunity to advance to the next career stage (i.e. promotion) (Lazear & Rosen 1981). A more recent study applies this tournament model to analyze promotions inside bureaucracies. Using resume data of provincial leaders in China, some scholars have found that provincial leaders' performance, which is measured by local GDP growth rates, has a positive and significant impact on their career advancement (Li & Zhou 2005). The use of GDP growth as a performance measure is based on the reasoning that provincial leaders in China are held responsible for local economic conditions, and a better economy of their locality sends a stronger signal of their abilities and performance.

Although the performance-based argument on job mobility and promotion sounds logical, there are several important issues to consider in evaluating this argument. First, although performance evaluation is an important part in promotion decisions, it ignores the fact that people may not have equal access to job opportunities even if they have the same qualifications and abilities, and certain groups may have better promotion chances than others, whereas some may have career ceiling no matter how well they perform. For example, Granovetter's (1995) seminal study has found that most of the people (70%) find job opportunities through their network and career contacts, instead of by direct application; and those who found jobs through personal contacts often fare better later on. More importantly, access to information and opportunity in labor markets is often related to one's network position. One could get

rich information sources from being a "broker" with many structural holes (Burt 1992), or simply hear from a high-status neighbor who has influence and access in networks. The phenomenon of unequal access to information and job opportunity is not well explained by the performance-based model, although we could imagine that the lack of access can directly impact one's future mobility and capacity of making a career transition.

Second, studies using the performance-based model often ignore the network effect by simply not examining networks, and they typically resort to two remedies. First, many studies use network "proxies," such as previous work experience, to approximate network effect, which often leads to biased estimates since they are not directly measuring networks (Li & Zhou 2005). Second, some studies dismiss networks by claiming that networks have no effect at all, with limited amount of testing (Landry, forthcoming). The lack of evidence on network effect is largely due to the difficulty in data collection and access to information inside organizations, which leads to a general lack of understanding about the network structures inside bureaucratic organizations.

Competing hypotheses to the performance model point out the importance of networks in career transitions. An argument of immediate relevance is the "structural hole" and brokerage theory, which states that having non-redundant ties would provide a broker with more diverse information. This, in turn, leads to better ideas and job performance, as well as more promotion opportunities inside organizations (Burt 2004). Although the theory of brokerage offers an interesting angle to look at the relationship between performance and promotion by adding the important element of networks, brokerage may not work in certain cultural context. Previous research points out that brokerage does not work in organizations that place higher values on collective effort and cooperation, and less emphasis on innovation and individual achievement (Xiao &Tsui 2007), which is a pertinent description of the organizational culture of a bureaucracy. We therefore expect that the benefit of brokerage would diminish in a bureaucratic context. Alternatively, other aspects of networks, such as social influence and sponsorship in networks, might be more relevant to one's career prospect inside bureaucracies, as the collectivist culture inside bureaucracies might place higher values on loyalty and strong connection to high-status players. This hypothesis has received supporting evidence, as research on labor market selection and transactional relations in China finds that sponsorship and early display of loyalty is highly important to one's career attainment (Li & Walder 2001), and government transactions often happen through patron-client relations (Oi 1985).

The crucial weakness of the sponsorship theory is that many of the studies that employ this argument do not have network data, again due to the inaccessibility of information. Much of the evidence comes from regression analysis and ethnographic accounts. An additional concern is that the sponsorship argument does not identify the network characteristics of people in sponsorship relations: how would we identify that two individuals are in a sponsorship relation, and what are the network characteristics of people with high-status sponsors?

The goal of our current study is to establish a direct comparison between the effects of networks and other career aspects, such as job performance, using a unique data set that provides rich information on bureaucratic career networks in China. We would like to investigate the following issues: first, what is the relative importance of networks versus performance in one's job transitions, and what network characteristics actually matter? Second, how does bureaucratic network evolve over time? Third, what kind of organizations provides employees with better mobility chances?

## III. Data

We use the Jiangsu Bureaucratic Mobility Database (JSBMD) to investigate the network patterns inside large bureaucracies. The first author collected the data in 2010 from government archives and local libraries in a major Chinese province (Jiangsu). The data contains job records of over 32,000 individuals over a period of 19 years (1990 - 2008) from 411 categories of government agencies and non-government organizations (260,000 person-year records). Job postings of the individuals spread across 14 different geographical locations within the province (13 cities and the provincial administration), and most of the individuals in the data are chief officials who are in charge of their offices. Detailed job records, such as office names, titles, bureaucratic ranks, locations and time of posting, are included in the data.

| | Individual Networks | | Organizational Network | |
|---|---|---|---|---|
| | **Mean** | **S.D.** | **Mean** | **S.D.** |
| Nodes | 18355 | (8660) | 411 | (0.0) |
| Edges | 177646 | (10770) | 2887 | (920) |
| Scc Size | 1 | (0.0) | 256 | (46.26) |
| Wcc Size | 17343 | (8998) | 306 | (37.7) |
| Modularity | 0.8141 | (0.04) | 0.53 | (0.034) |
| Clustering Coeff. | 0.769 | (0.055) | 0.221 | (0.047) |
| Ave. Path Length | 7.32 | (1.717) | 3.71 | (0.303) |
| Diameter | 16 | (2.83) | 7 | (0.0) |

**Table 1. Properties of Individual & Organizational Networks**

From the data, we construct two types of networks. First, we construct individual networks over time from the yearly job records, in which the nodes are individuals and edges are based on people's co-working experience. Two individuals are counted as having an edge if they work in the same office at the same time and location, and edges are undirected. The edge weights are years of co-working experience, which are further transformed by three functions, logarithmic, geometric, inverse exponential, to test whether including weights in calculating network properties would increase the accuracy of prediction. Second, we construct organizational networks based on job mobility of individuals among different workplaces. The nodes in this network are bureaucratic agencies, and agencies of the

same name but in different locations are treated as the same node. Two organizations share a directed edge if there are job transfers from one to the other. The edge weights are transition probabilities of job transfer between pairs of organizations. The summary statistics of each network are presented in Table 1.

## IV. Algorithms and Models

The main purpose of this project is to predict promotion in bureaucratic careers using network properties, in comparison to results based on conventional non-network measures (such as job performance). The dependent variable is promotion, which is coded as a binary indicator function with value 1 if a person is promoted in a given year and 0 otherwise. Overall, promotion is a rare event, as only 5% of the observations have had a promotion event. The key independent variable for non-network aspects is annual GDP growth rate, which is typically used to indicate job performance, especially for elite bureaucrats who hold leadership positions as they are in charge of regional economies. Since GDP growth rate is an endogenous variable (i.e. the variable is correlated with the error term in the regression model, which yields biased estimate), we use exogenous variables as instruments to adjust for the bias. The instruments include exogenous shock events (e.g. establishing new cities), region and year fixed effects, and administration types of the regions. In addition to GDP growth rates, we include a set of control variables to reduce unobserved heterogeneities among different regions, career lines, and job characteristics.

### 4.1 Algorithms for Individual Networks

We use PageRank and community detection algorithm to investigate properties of individual networks. The key variables here are PageRank and community homogeneity measured by Herfindahl index (HHI). Our main hypotheses involve the impact of sponsorship and community homogeneity on career mobility. We hypothesize that 1) having important sponsors facilitates promotion and career advancement (**sponsorship hypothesis**), whereas 2) entrenchment in a relatively homogenous community hinders career mobility (**community homogeneity hypothesis**).

PageRank algorithm measures the relative importance of an individual in the network based on importance of his neighbors. It employs a recursive algorithm defined by

$$r_j = \sum_{i \to j} \beta \frac{r_i}{d_i} + (1-\beta)\frac{1}{n} \qquad (1)$$

where $r_i$ is the PageRank score of $j$'s neighbor $i$, $d_i$ is the outdegree of $i$, and $1-\beta$ is the probability of jumping to another random node in the network (Brin & Page 1998). Since the PageRank algorithm defines a node's importance based on his neighbors' importance, it is appropriate for testing the sponsorship hypothesis. Specifically, individuals with high-status sponsors who have more selective connections would receive higher PageRank scores. We compare the model prediction from PageRank with those using alternative measures that capture similar information to check the robustness of this measure. In addition, we compare the results from PageRank and betweenness centrality to examine whether sponsorship or brokerage is more important to one's bureaucratic career prospect.

An important topic in network analysis is the effect of tie strength on channeling information and resources in career mobility (Granovetter 1995). In order to test whether tie strength matters in sponsorship relations, we use years of co-working experience to approximate tie strength between a pair of individuals, with the assumption that longer period of co-working leads to stronger relationships. Using years of co-working experience, however, is quite noisy for approximating tie strength, since this weight assignment assumes that tie strength increases linearly over time and ranges between [1, 19]. In order to derive more accurate ranges of edge weights, we use three functions to transform years of co-working experience. We first use the logarithmic function to transform weights, where weight assignment follows $W = 1 + \ln T$, and $T$ being the number of co-working years, $W \in [1, 1+\ln 19] = [1, 3.944]$. Second, we use a geometric series to transform the edge weights, $W = \sum_{t=1}^{T} 2^{-(t-1)} = 2 - 2^{-T+1} \leq 2$, and weights are distributed between [1, 2]. Third, we use an inverse exponential function to transform the edge weights, $W = \sum_{t=1}^{T} e^{-(t-1)} = \frac{1-e^{-n}}{1-e^{-1}} \leq (1-e^{-1})^{-1} \approx 1.582,\ W \in [1, 1.582]$. We observe that the year weights are by far the noisiest, whereas the inverse exponential transformation yields weights with the smallest standard errors and are closest to 1.

We use the modularity algorithm with Clauset-Newman-Moore method for community detection in individual networks (Clauset et al. 2004). The modularity of partitioning S of a graph G is defined as

$$Q(G,S) = \frac{1}{2m}\sum_{s\in S}\sum_{i\in S}\sum_{j\in S}\left(A_{ij} - \frac{k_i k_j}{2m}\right) \qquad (2)$$

where $2m$ is a normalizing constant which constrains $Q(G,S) \in [-1, 1]$, with $m$ being the number of edges in the network; $A_{ij}$ is the number of edges within group $s$, and $\frac{k_i k_j}{2m}$ is the expected number of edges within group $s$ based on random re-assignment of edges. A key intuition about the individual network is that communities are likely to be bounded by geographical locations, since most of the individuals in the data have bureaucratic careers that are relatively stable and do not span across different locations. We speculate that most of the communities would display a high level of homogeneity in terms of members' geographical profiles, although communities that are very large tend to have more heterogeneity since there is a higher chance of including members from different locations. To capture this idea, we use the Herfindahl index (HHI) to characterize geographical heterogeneity / homogeneity within each community. The HHI is defined as

$$H = \sum_{i=1}^{N} s_i^2,\ H \in [0, 1] \qquad (3)$$

where $s_i$ is the fraction of people from a given location within a community. Higher HHI value indicates greater homogeneity of a community, since there would be larger fractions of members from the same locations. We expect to observe that communities with higher geographical homogeneity offer lower mobility rates since stronger community boundaries would impose more constraint on members' movements.

### 4.2 Algorithms for Organizational Networks

In order to identify the organizations that are likely to offer better mobility chances, we model the network connections among bureaucratic agencies with a discrete-time Markov Chain (DTMC). A DTMC is a stochastic process characterized by the memorylessness property, i.e. situation of the current state depends only on the immediate previous state and not on any other states. By conceptualizing organizations as Markov chain states, we construct transition matrix for each year and calculate the transition probabilities between pairs of organizations. The transition probabilities are expressed as $P_{ijt} = \frac{n_{ijt}}{\sum_{k=1}^{N} n_{ikt}}, i \neq j$, where $n_{ijt}$ is the number of people who change job from workplace $i$ to $j$ at time $t$, and $\sum_{k=1}^{N} n_{ikt}$ is the total number of people at workplace $i$ or change jobs from workplace $i$ at time $t$. We also add an absorbing state to each matrix to make it row-stochastic (i.e. rows sum up to 1).

A key observation is that organizational connections are subject to less geographical constraint, since we group together agencies of the same names but in different locations. This grouping is based on our goal to investigate the general pattern of job transitions among organizations irrespective of their geographical variation. As a result, it is likely that the community boundaries are relatively weak in the organizational network, and we may observe an overlapping community structure in which the same organizations have multiple community affiliations. Following this reasoning, we use overlapping community detection algorithm to partition the organizational network. We hypothesize that 1) organizations with more community affiliations offer better job mobility and promotions (**organizational membership hypothesis**), and 2) community affiliations are positively correlated with higher status for a given organization (**membership and status hypothesis**). Furthermore, 3) organizations with multiple affiliations are likely to be large generalists that engage in personnel exchange with members of diverse communities (**generalist hypothesis**).

We use the BIGCLAM algorithm for overlapping community detection (Cluster Affiliation Model for Big Networks, Yang & Leskovec 2013). BIGCLAM is an example of bipartite affiliation network model, in which nodes are affiliated to their communities and links of the network are derived based on nodes' community affiliations. The algorithm formulates community detection as a variant of non-negative matrix factorization (NMF) and discovers nodes' community membership factors using maximum likelihood estimation (Yang & Leskovec 2013:2). We derive the community affiliations of organizations from the yearly transition matrices using BIGCLAM, and then compute the number of community affiliations for each organization over time as organizational memberships.

We check the correlations between network centralities and community memberships derived from the transition matrices to test the hypothesis that organizations with more memberships tend to have higher status. We calculate the weighted degree centralities and PageRank based on transition probabilities and modify the Floyd-Warshall algorithm for calculating weighted node betweenness in a directed network (Floyd 1962). A geodesic between a pair of nodes in a transition matrix is defined as the path with the largest N-step transition probability (i.e. multiplication of transition probabilities over each step). Since each pair of nodes has exactly one geodesic in between due to the uniqueness of transition probabilities, node betweenness is simply the number of geodesics that pass through a node:

$$g(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} = \sum_{s \neq v \neq t} \sigma_{st}(v) \quad (4)$$

We hypothesize that more membership affiliations is correlated with higher organizational status based on centrality measures, as organizations with more memberships are likely to have more neighbors, connect shortest paths and display greater influence in the network.

To capture the idea that organizations with more community affiliations are likely to be large generalists that engage in activities with diverse members, we use Shannon entropy to measure the heterogeneity in personnel flow among organizations. Shannon entropy is defined as

$$H(X) = E[I(X)] = E[-\ln(P(X))] \quad (5)$$

where $I(X)$ is the information content of $X$, and $X$ is the row or column vector of transition probabilities for a given organization. Shannon entropy captures the heterogeneity in job transfers by measuring the unpredictability of information content of transition probabilities. We expect that organizations with more community memberships would display greater entropy (i.e. heterogeneity) in their employees' career mobility.

For the purpose of visualizing the general pattern of organizational networks, we approximate a time-homogenous Markov chain from our yearly transition matrices using Monte Carlo simulation. The naïve method in approximation is to take the cumulative transition probabilities, $P_{ijT} = \frac{\sum_{t=1}^{T} n_{ijt}}{\sum_{t=1}^{T}\sum_{k=1}^{N} n_{ikt}}, i \neq j$, where $\sum_{t=1}^{T} n_{ijt}$ is the total number of people that change jobs from organization $i$ to $j$ for all time, and $\sum_{t=1}^{T}\sum_{k=1}^{N} n_{ikt}$ is the total number of people who have worked at $i$ for all time. The cumulative method would flatten out some of the noises in transition matrices; however, it tends to over-count transition probabilities if organization sizes do not change and transitions happen occasionally (e.g. suppose an organization has only 2 people for all time, and one of them changes job at time $t$. The cumulative transition probability would be 0.5 after time $t$ although the transition happens only once). A more robust method is to use Monte Carlo simulation on the yearly transition matrices: we construct a list of transition probabilities for each pair of organizations from all transition matrices (excluding the absorbing state), and then randomly sample the transition probabilities for each pair of organizations over 10,000 iterations. We then add an absorbing state to the simulated matrix to make it row-stochastic. The simulation results are expected to yield more consistent estimates of transition probabilities compared to those from the cumulative method.

### 4.3 Models

We use a random-effects Probit model with robust standard errors to estimate the effects of covariates on the binary outcome, promotion. A Probit model takes the functional form

$$P(Y = 1|X) = \Phi(X'\beta) \quad (6)$$

where $\Phi$ is the cumulative density function (CDF) of the standard normal distribution, and the parameters are estimated using maximum likelihood estimation (MLE). The Probit model is motivated as a latent variable model. Suppose there is a random variable

$$Y^* = X'\beta + \varepsilon,\ \varepsilon \sim N(0,1) \quad (7)$$

where $Y^*$ can be observed when it is positive and not observable otherwise:

$$Y = \begin{cases} 1\ if\ Y^* > 0 \\ 0\ otherwise \end{cases} \quad (8)$$

Then the probability of observing $Y$ is $P(Y = 1|X) = P(\varepsilon > -X'\beta) = P(\varepsilon < X'\beta) = \Phi(X'\beta)$, which agrees with equation (6). The random-effects Probit model is a modified version of the Probit model that takes into account the autocorrelated error terms in panel data. It is an appropriate modeling strategy given our binary outcome variable and panel data structure.

## V. Results

### 5.1 Individual PageRank and Community Homogeneity

Figure 1 illustrates the PageRank scores for individuals of different positional ranks and status. We divide individuals into groups following two criteria. In the left panel, individuals are grouped on their formal job ranks into high rank, mid rank, and low rank. In addition, individuals who do not work in government agencies but are employees of state-owned enterprises or public institutions are grouped into the "non-government" category. We observe that high rank individuals' PageRank score is significantly higher than others, followed by mid rank officials; there is almost no difference between low rank and non-government individuals. This shows that PageRank score increases with formal rank and file. In the right panel, we divide individuals based on political elite status, and political elites are defined as those who serve as top officials in an administration, which include provincial governors, city mayors, county chiefs, and communist party secretaries of each level.

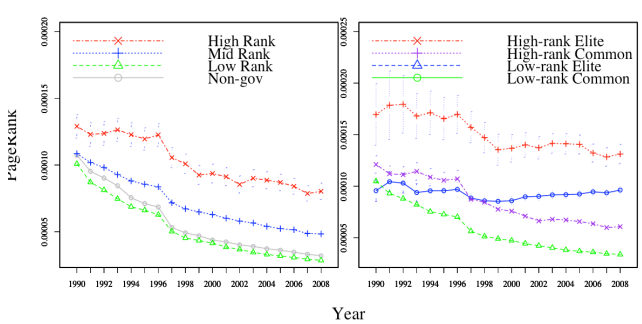


**Figure 1. PageRank Scores for Different Groups**

Comparing the PageRank score of political elites with their counterparts of the same rank, we observe that the PageRank scores of elites are significantly higher than non-elite bureaucrats of the same rank. The PageRank scores of low-level elites even surpass non-elite officials of higher ranks after 1997. This means that higher status individuals also have higher PageRank in the network when controlling for formal rank and file. In fact, if we look at the identities of those who have the highest PageRank scores, they are invariably high-ranking officials in major offices (e.g. Zhuang Shen, the former vice mayor of Wuxi; Gao Dezheng, the former standing committee member in provincial Communist Party; and Dai Shunzhi, the former Communist Party secretary of Nanjing).

Figure 2 illustrates the community structure in the cumulative network over 19 years. We observe that there is a perfect correlation between the number of largest communities and the number of geographical locations in the data (14 largest communities and 14 locations), and it is highly probable that communities are geographically bounded. Figure 3 illustrates the evolution and properties of communities in individual networks. A closer look at the community structures shows that the number of communities fluctuates over time and peaks in 1998, due to the inclusion of new data that became available after 1998 (Figure 3 top left). Small communities, however, die out fast as the age of small communities is relatively short (age here being the number of years that a community exists in the data) (Figure 3 top right). Using conductance to diagnose the quality of communities (Leskovec et al. 2008), we find that the best community size occurs at 100 (Figure 3 bottom left). This is understandable given that communities with sizes less than 100 are likely to die early, whereas communities with sizes too large are likely to absorb more heterogeneity. We observe a decreasing trend of community homogeneity when plotting the HHI index on community size, which further corroborates the idea that large communities are likely to absorb more heterogeneity. However, some communities display a faster trend of decreasing homogeneity over size, and a closer look reveals that these communities typically include a large portion of non-government employees in financial institutions who change jobs across different locations (Figure 3, bottom right). The mobility pattern of non-government employees could be an interesting topic for future studies.

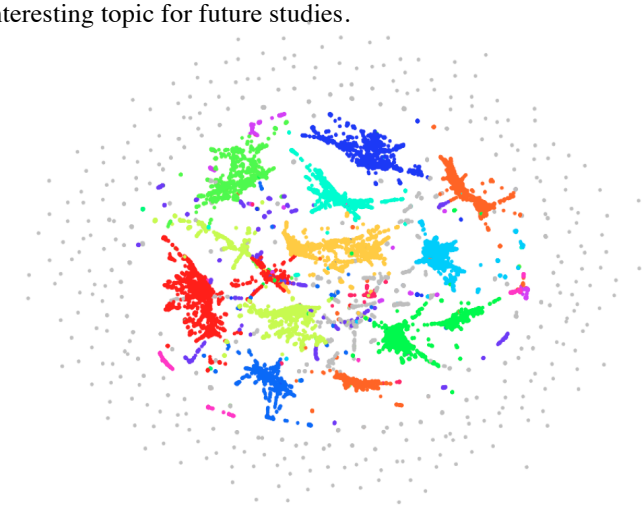

**Figure 2: Community Detection in the Network, Cumulative over 1990 – 2008**

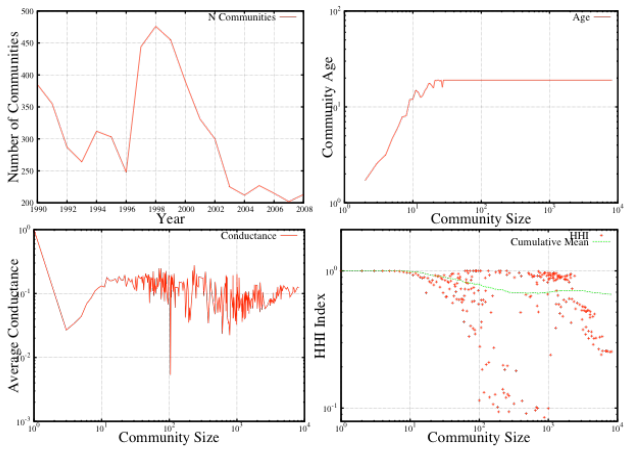


**Figure 3. Evolution of Communities Detected by Modularity Algorithm on Individual Networks (Clauset-Newman-Moore Method)**

### 5.2 Organizational Memberships

Figure 4 illustrates the correlation of organizational membership derived from the BIGCLAM algorithm with centrality measures and Shannon entropy. We observe a high correlation between organizational membership and indegree centrality ($\rho = .75$), whereas the correlation between membership and outdegree is not very high ($\rho = .38$) (Figure 4, top left). This indicates that organizations with more membership affiliations are likely to be the receiver of job transfers rather than the sender, which makes intuitive sense since high-status nodes are more likely to receive inlinks than sending outlinks. On the other hand, organizational memberships do not have a high correlation with node betweenness ($\rho = .30$, Figure 4 top right) but are highly correlated with PageRank ($\rho = .67$, Figure 4 bottom left). This means that organizations with more memberships tend to have higher influence in the network, although they do not necessarily connect shortest paths.

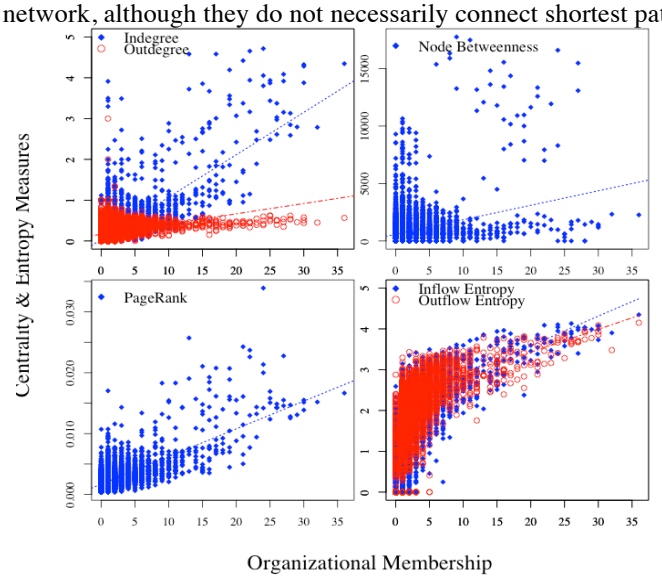


**Figure 4. Organizational Membership on Centrality & Entropy**

In addition, organizations' membership affiliations are highly correlated with Shannon entropy ($\rho = .7$, Figure 4 bottom right), which indicates that overlapping community memberships of an organization increase the heterogeneity in employees' career mobility. In sum, we conclude that organizations with multiple affiliations to overlapping communities are likely to have higher status and influence in the network, as well as being generalists that regularly interact with members from diverse communities.

In order to develop further insight into the kind of organizations that are likely to have multiple membership affiliations, we explore the general pattern of organizational connections based on results from the Monte Carlo simulation on transition matrices. We construct a multiplex network with three layers according to the administrative divisions of organizations, as some of the organizations belong to the provincial administration, and others to city and sub-city (county and district) administrations. Visualization of the multiplex networks shows that the networks appear to be organized around four hubs, the Chinese Communist Party (CCP), government (GOV), Local People's Congress (LPC), and Chinese Political Consultative Conference (CPPCC), which are indeed organizations of the highest status by definition of formal bureaucratic rank (Appendix 4; note that we have incomplete data on sub-city level organizations, while city- and provincial-networks present a more systematic picture). Interestingly, these four hubs also have the highest PageRank scores in each layer of the network.

Next, we compare results of network partitioning from BIGCLAM with conventional community detection algorithm (modularity) on the simulated transition matrix. We find that the modularity algorithm differentiates organizations according to administrative divisions, i.e. the network is partitioned into clusters of provincial, city and sub-city level organizations (Figure 5 top panel). BIGCLAM, on the other hand, detects organizations that are at the center of overlapping communities. It has found 95 overlapping communities among 411 organizations, and two of the organizations have over 40 community affiliations. They are the city government and Chinese Community Party, the highest-status agencies among sub-provincial organizations (center two nodes in Figure 5 bottom panel). This result shows that BIGCLAM is superior for detecting the central players in network communities compared to the conventional methods, which could only pick up information that is less refined.

So far, our general findings regarding the organizational networks suggest that membership affiliations in overlapping communities is a signal of status, as organizations with more community affiliations tend to have higher influence in the network and provide heterogeneous career opportunities to its employees in terms of job mobility. We will further test the effect of network characteristics and organizational memberships on promotion in regression analysis as follows.

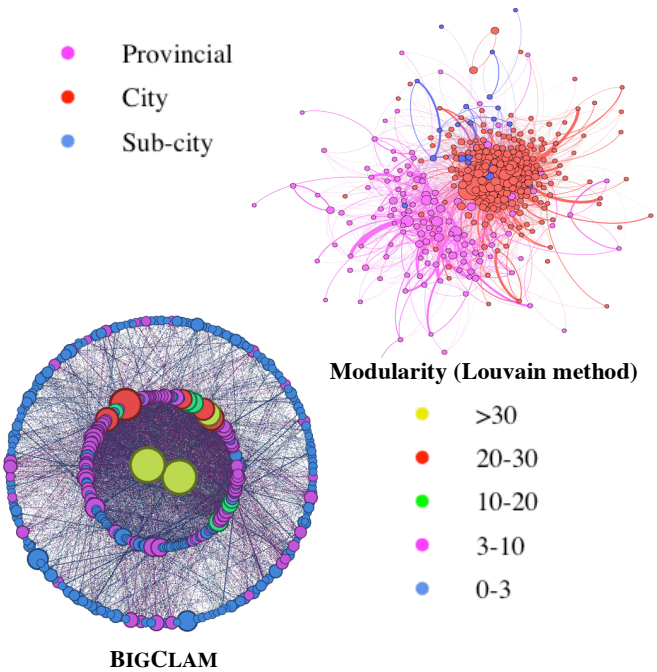


**Figure 5. Community Detection Results by Modularity (Louvain method) and BIGCLAM on Organizational Networks. Node Size is Proportional to PageRank. Node coloring is according to administrative division (top) and number of organizational memberships (bottom)**

### 5.3 Regression Output

The regression estimates are presented in Appendices 1 - 3. We first use single-regressor models with different model specifications (linear probability, random-effects Probit, and survival analysis) to investigate the sensitivity of our main independent variables (economic performance and individual network centralities) (Appendix 1). The effect of growth rate is relatively stable across different model specifications, whereas some of the network centralities demonstrate different behaviors across different models. For example, whereas betweenness centrality is positive and significant in linear probability and Probit models, it is negative in survival models. The alternative measures to PageRank (alpha centrality, Bonacich power centrality, and eigenvector centrality) are not statistically significant for most of the models. PageRank, by far, is the most robust network predictor with the largest effect size as its directions and significant levels are consistent across models ($p < 0.001$). We thus proceed to use PageRank as our main predictor to test the sponsorship hypothesis.

Next, we use nested models to compare model fit when adding our main predictors of promotion. Column 1 of Appendix 2 presents a model with only control variables that measure job characteristics and local economic conditions. Only 35% of the promotion events are predicted accurately in this model. Column 2 adds the economic performance variable, which has a positive effect and significantly improves the model according to a Wald test (Wald $\chi^2_{(1)} = 23.25, p < 0.001$). The prediction accuracy increases to 61%. We add our main network predictors of individual PageRank and community homogeneity (HHI) in column 3. Both variables have significant effects in the expected direction (PageRank positive and HHI negative), and the model fit improves significantly (Wald $\chi^2_{(2)} = 1024.23, p < 0.001$). The prediction accuracy of promotion increases to 91%. In column 4, we add the organizational membership derived from BIGCLAM to test the effect of workplace status indicated by community affiliations, and the effect is positive and highly significant. The model fit further improves (Wald $\chi^2_{(1)} = 892.27, p < 0.001$) and the prediction accuracy increases to 95%. Overall, the three variables derived from individual and organizational networks have strong predictive power on promotion outcomes, and their effect sizes are larger than the non-network variables, such as economic performance. The coefficient estimates of the main variables from the full model (column 4, Appendix 2) are presented in the left panel of Figure 6.

We now turn to investigate the importance of tie strength by calculating PageRank with different edge weight functions (columns 5 – 8 in Appendix 2). We find, however, that the effect of the un-weighted PageRank is by far the largest, and PageRank scores with weights closer 1, such as those with weights transformed by the inverse exponential function and geometric series, have larger effects than others. The Bayesian Information Criterion (BIC) for non-nested model comparison shows that the model with the unweighted PageRank has the best model fit relative to those with weighted PageRank scores (columns 5 - 8), and the prediction accuracy of models with weighted and un-weighted PageRank are about the same (around 93 – 95%). We conclude that adding weights in PageRank does not improve model prediction. A potential reason is that the length of co-working experience could be a measure of immobility rather than connection strength, while it is also possible that tie strength matters less to promotion decisions than the fact of knowing a high-status person.

Finally, we consider the effectiveness of our main predictors on promotion in multi-layered networks. We estimate the effects of the performance and network variables on promotion of people in different positional ranks and status (Appendix 3). The coefficient estimates are presented in Figure 6 (middle and right panels). We observe from Figure 6 that the economic performance variable has inconsistent effects for the promotion of people in different positional ranks. Non-government and low-rank individuals receive no benefit from better economic growth, whereas mid- and high-rank officials benefit from positive economic growth (Figure 6 middle panel, first row). Furthermore, economic growth is irrelevant to non-elites' promotion, which is expected given that non-elite officials are not responsible for regional economies. Elite officials receive benefits in promotion from higher economic growth, as regional economic growth is part of their job evaluation (Figure 6 right panel, 1st row).

As for the network variables, PageRank consistently has a positive effect on the promotion of officials of different ranks and elite status, whereas community homogeneity consistently decreases one's mobility chances (Figure 6 middle

and right panels, 2nd & 3rd row). Organizational membership has a positive effect except for non-government people, who are probably subject to different promotion criteria than government employees (Figure 6 middle and right panels, 4th row). This is supported by the different community characteristics of non-government individuals compared to others as mentioned before, as well as the poor prediction accuracy of their promotion by the model (18%). On the other hand, the model performs reasonably well in predicting the promotion of government employees, as the prediction accuracy is 82% for low-rank employees and over 99% for mid- and high-rank officials. In addition, the prediction accuracy is 90% and 99% for elite and non-elite individuals respectively. This shows that our model is particularly suited for predicting the promotion of high-status individuals inside government bureaucracy.

Overall, our regression results confirm each of the hypotheses regarding sponsorship, community homogeneity and organizational membership. Having important sponsors in political career is critical for future advancement, whereas entrenchment in a relatively homogenous community constrains one's career options. Working in an important organization that has multiple community affiliations also increases one's mobility chances, as employees of well-connected workplaces are likely to get access to diverse resources and opportunities.

### 5.4 Evolution of Networks

We now turn to explore some evolutionary patterns of individual networks in order to gain more insight into the data. The degree distributions of the network over time are plotted in Figure 7, and the tail of the distribution follows a power law with $\alpha \approx 2$ (Barabasi & Albert 1999). The degree distributions stabilize after 10 years, as the distribution histograms after 2000 overlap to a large extent. The head of the distributions do not seem to follow a power law and we can fit the curves later with a log-normal or power law with exponential cutoff to estimate the distribution parameters.

Next, we examine some of the basic properties of network expansion over time. We observe from Figure 8 that the bureaucratic network expands following a densification power law with $\alpha = 1.35$ (Leskovec et al. 2007). The average degree increases over time, whereas the average path length decreases over time due to densification of edges in a power-law graph.

The most interesting plot is the network diameter change over time. The diameter first decreases and then spikes up during the period 1999 - 2002, when there is a major political disturbance in the central regime: the change of presidency in China.

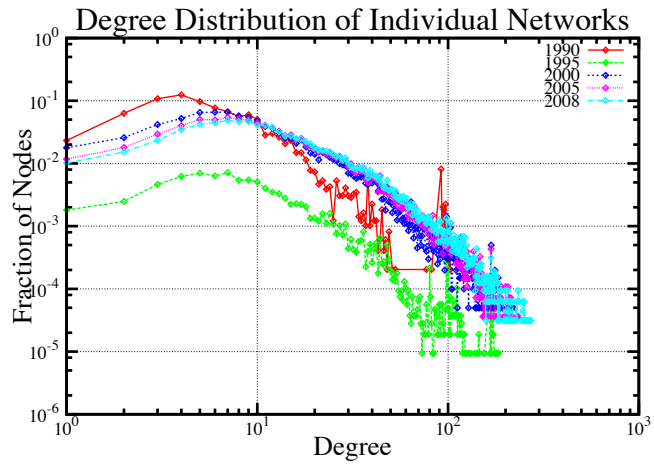


**Figure 7. Degree Distributions on a Log-log Scale**

Initially we suspect that some important (high-degree) nodes might be removed from the networks due to political disturbance, but our networks are cumulative, so nodes do not drop out of the graphs after entrance. We further suspect that the diameter increase is due to the entrance of non-government individuals in the data after 2000, since many new business organizations established around that period and non-government individuals tend to be isolates. We re-plot the network diameter after dropping the non-government individuals, and the same pattern persists.

In order to examine the network diameter change more closely, we split the networks into multiple layers based on rank and elite status. We first split the networks based on formal positional rank, and each network layer includes only edges among individuals of the same rank (i.e. low-rank to low-rank, mid-rank to mid-rank, and so on). We find that high-rank individuals generally have shorter diameter and path lengths among each other, followed by mid-rank and low-rank individuals (Figure 9, top panels). Network diameters fluctuate over time whereas average path lengths display a decreasing

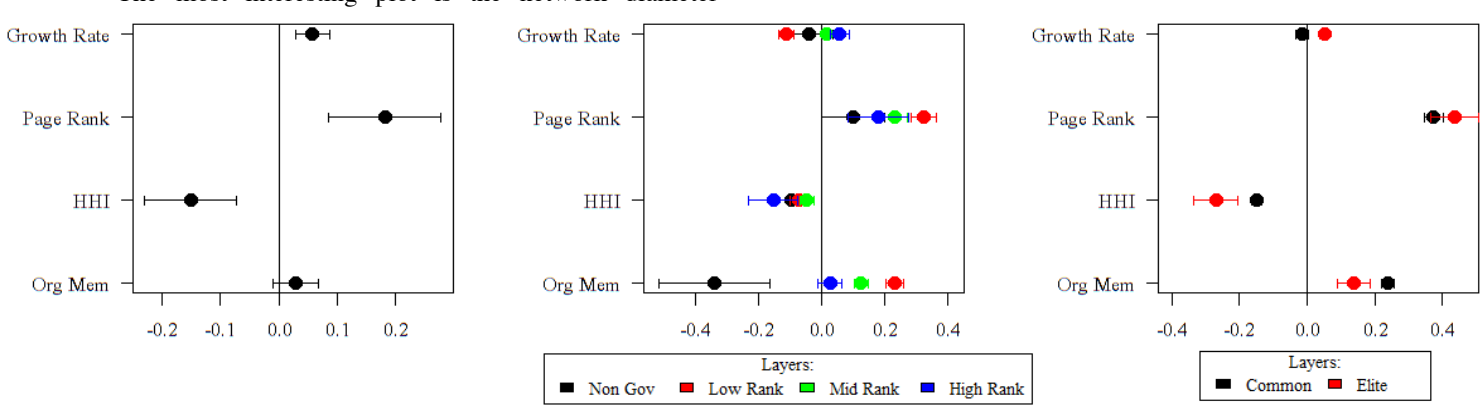


**Figure 6. Coefficient Estimates from Random-effects Probit Models**

trend for government officials. The diameter and path length, however, expand before 2002 for non-government individuals, which suggests that the network evolution patterns are different for government and non-government employees.

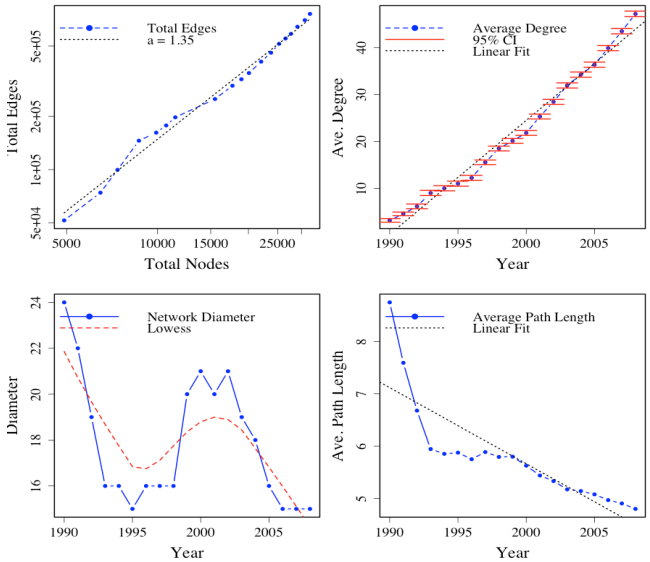


**Figure 8. Network Evolution: Properties of Network over Time**

Second, we construct layers among individuals of different positional ranks (i.e. low rank to mid rank, mid rank to high rank, and low rank to high rank). We find that high-rank individuals are generally more reachable in the network as they have shorter diameter and path lengths to people of other ranks, whereas low- and mid- rank officials are in general much harder to connect (Figure 9, middle panels). This finding is counterintuitive at first sight, as people would generally expect that high-status individuals are harder to reach than lower-status individuals. From a network perspective, however, this result is quite easy to interpret given that high-rank individuals have higher degrees, which render them reachable in shorter steps.

In addition, we construct multiplex network based on elite status with three layers: elite-to-elite, elite-to-common (non-elite), and common-to-common. We find that the diameter and path length among elites are much shorter than others, which means that political elites are a more inter-connected group than common bureaucrats (Figure 9, bottom panels). The above findings all lend to the theory that individuals of high status serve as hubs in networks, and they are essential to cluster formation in networks for connecting nodes that are otherwise isolated.

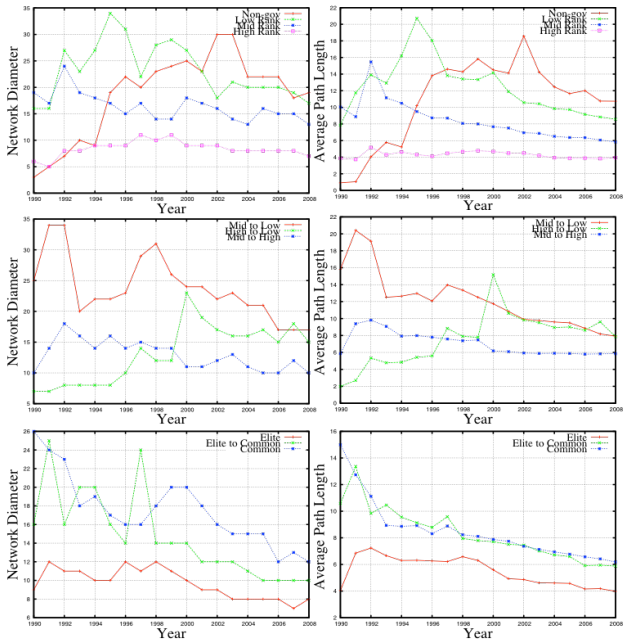


**Figure 9. Diameter and Average Path Length for Network Layers**

## VI. Conclusion

Our study has found conclusive evidence that networks inside a large bureaucracy have significant impact on individuals' career mobility and advancement. To summarize, individuals with high-status sponsors are likely to obtain better promotion opportunities, whereas community homogeneity constrains one's career movement. Working in a high-status organization that has multiple community affiliations also increases one's chance of promotion, as employees in such organizations are likely to have access to diverse career options and important contacts.

There are several future directions that are worth investigation. First, what are the differences in mobility trajectories for government and non-government employees? Our study has repeatedly identified the oddity in career mobility of non-government employees, perhaps due to incomplete sampling of this group of individuals in government archives. However, some of the job characteristics of non-government employees, such as the relatively high geographical mobility of financial elites, are still interesting and worth future exploration. Second, how would we characterize the change in connective patterns of bureaucratic agencies over time? So far, we have simulated a time-homogenous Markov chain for visualizing organizational connections, but the connection pattern might be time-dependent. The analysis of a time-inhomogeneous Markov chain would be an impending task for future analysis on the evolution of organizational networks.

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## Appendix 1. Single Regressor Models, with Fixed-Effects Linear Probability, Random-Effects Probit, and Survival Models

| | (1) | | | (2) | | | (3) | | | (4) | | | (5) | | | (6) | | | (7) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **LP** | **Probit** | **Survival** | **LP** | **Probit** | **Survival** | **LP** | **Probit** | **Survival** | **LP** | **Probit** | **Survival** | **LP** | **Probit** | **Survival** | **LP** | **Probit** | **Survival** | **LP** | **Probit** | **Survival** |
| Annual Growth Rate | 0.006*** | 0.033*** | 0.036*** | | | | | | | | | | | | | | | | | | |
| | (0.001) | (0.004) | (0.003) | | | | | | | | | | | | | | | | | | |
| Degree | | | | 0.008*** | 0.174*** | -0.032*** | | | | | | | | | | | | | | | |
| | | | | (0.001) | (0.004) | (0.006) | | | | | | | | | | | | | | | |
| Betweenness | | | | | | | 0.001 | 0.088*** | -0.013** | | | | | | | | | | | | |
| | | | | | | | (0.001) | (0.007) | (0.005) | | | | | | | | | | | | |
| Alpha Centrality | | | | | | | | | | 0.000 | 0.001 | 0.009 | | | | | | | | | |
| | | | | | | | | | | (0.000) | (0.002) | (0.010) | | | | | | | | | |
| Bonacich Power Centrality | | | | | | | | | | | | | 0.000 | 0.002 | 0.013 | | | | | | |
| | | | | | | | | | | | | | (0.000) | (0.005) | (0.011) | | | | | | |
| Eigenvector Centrality | | | | | | | | | | | | | | | | 0.003 | 0.002 | -0.020** | | | |
| | | | | | | | | | | | | | | | | (0.002) | (0.005) | (0.006) | | | |
| Page Rank | | | | | | | | | | | | | | | | | | | 0.060*** | 0.191*** | 0.086*** |
| | | | | | | | | | | | | | | | | | | | (0.002) | (0.004) | (0.006) |
| Constant | 0.047*** | -1.719*** | | 0.049*** | -1.686*** | | 0.049*** | -1.690*** | | 0.049*** | -1.712*** | | 0.049*** | -1.712*** | | 0.049*** | -1.712*** | | 0.049*** | -1.719*** | |
| | (0.000) | (0.007) | | (0.000) | (0.006) | | (0.000) | (0.007) | | (0.000) | (0.007) | | (0.000) | (0.007) | | (0.000) | (0.007) | | (0.000) | (0.007) | |
| Observations | 183,136 | 183,136 | 154,289 | 204,279 | 204,279 | 172,065 | 204,279 | 204,279 | 172,065 | 204,279 | 204,279 | 172,065 | 204,279 | 204,279 | 172,065 | 204,279 | 204,279 | 172,065 | 204,279 | 204,279 | 172,065 |

Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. All variables are standardized for comparing effect size.

## Appendix 2. Estimates from Nested Probit Models that Test Variable Effects and Model Fit

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| [a] **Performance** | | | | | | | | |
| Annual Growth Rate (instrumented) | | 0.047*** | 0.019** | 0.015** | 0.033*** | 0.026*** | 0.022*** | 0.020*** |
| | | (0.004) | (0.006) | (0.005) | (0.004) | (0.005) | (0.005) | (0.005) |
| [a] **Individual Network** | | | | | | | | |
| Page Rank (unweighted) | | | 0.419*** | 0.402*** | | | | |
| | | | (0.014) | (0.013) | | | | |
| Page Rank (year) | | | | | 0.156*** | | | |
| | | | | | (0.009) | | | |
| Page Rank (log) | | | | | | 0.238*** | | |
| | | | | | | (0.010) | | |
| Page Rank (geometric) | | | | | | | 0.283*** | |
| | | | | | | | (0.011) | |
| Page Rank (inv. exponential) | | | | | | | | 0.316*** |
| | | | | | | | | (0.012) |
| Community Homogeneity (HHI) | | | -0.174*** | -0.157*** | -0.077*** | -0.106*** | -0.121*** | -0.131*** |
| | | | (0.008) | (0.008) | (0.007) | (0.007) | (0.007) | (0.007) |
| [a] **Organization Network** | | | | | | | | |
| Organization Memberships | | | | 0.249*** | 0.241*** | 0.243*** | 0.245*** | 0.246*** |
| | | | | (0.008) | (0.007) | (0.008) | (0.008) | (0.008) |
| **Controls** | Y | Y | Y | Y | Y | Y | Y | Y |
| **Constant** | -1.744*** | -1.752*** | -1.704*** | -1.513*** | -1.506*** | -1.500*** | -1.501*** | -1.504*** |
| | (0.021) | (0.021) | (0.025) | (0.025) | (0.022) | (0.023) | (0.023) | (0.024) |
| [b] **Wald $\chi^2_{(k)}$** | $2336.30_{(15)}$ | $123.25_{(1)}$ | $1024.23_{(2)}$ | $892.27_{(1)}$ | | | | |
| [c] **BIC** | 63959.23 | 63841.63 | 61079.75 | 59947.04 | 61767.03 | 61302.55 | 60989.14 | 60730.43 |
| **Observations** | 154,287 | 154,287 | 152,901 | 152,901 | 152,901 | 152,901 | 152,901 | 152,901 |
| **N. Individuals** | 25,492 | 25,492 | 25,357 | 25,357 | 25,357 | 25,357 | 25,357 | 25,357 |

Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05

[a] Network and performance variables are standardized to be comparable in effect size. Annual growth rate is instrumented following the two-stage least square procedure. The instruments include exogenous variables such as shock events, administration, region and year fixed effects. This will yield unbiased estimates.

[b] Wald $\chi^2$ is compared with the previous model for nested model fit improvement.

[c] Bayesian Information Criterion (BIC) for comparing non-nested model fit. The smaller the BIC statistic is, the better the model fit is. Evidence against higher BIC statistic follows the rule: 0 – 2: no evidence; 2 – 6: positive; 6 – 10: strong; > 10: very strong.

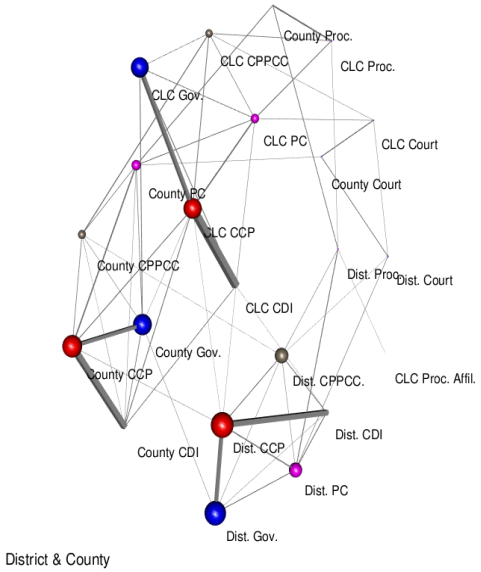
**Appendix 3. Probit Estimations for Each Network Layer**

| | By Rank | | | | By Elite Status | |
|---|---|---|---|---|---|---|
| | **Non-gov** | **Low Rank** | **Mid Rank** | **High Rank** | **Common** | **Elite** |
| **Performance** | | | | | | |
| Annual Growth Rate (instrumented) | -0.040 | -0.110*** | 0.016** | 0.058*** | -0.016 | 0.051*** |
| | (0.038) | (0.012) | (0.006) | (0.015) | (0.009) | (0.007) |
| **Individual Network** | | | | | | |
| Page Rank (unweighted) | 0.100* | 0.327*** | 0.232*** | 0.182*** | 0.374*** | 0.436*** |
| | (0.050) | (0.020) | (0.020) | (0.048) | (0.014) | (0.035) |
| Community Homogeneity (HHI) | -0.094*** | -0.071*** | -0.045*** | -0.151*** | -0.149*** | -0.270*** |
| | (0.028) | (0.013) | (0.011) | (0.039) | (0.008) | (0.033) |
| **Organizational Network** | | | | | | |
| Organization Memberships | -0.337*** | 0.232*** | 0.126*** | 0.029 | 0.238*** | 0.139*** |
| | (0.088) | (0.014) | (0.011) | (0.019) | (0.009) | (0.024) |
| **Controls** | Y | Y | Y | Y | Y | Y |
| **Constant** | -2.286*** | -1.337*** | -0.994*** | -1.269*** | -1.490*** | -1.071*** |
| | (0.130) | (0.039) | (0.033) | (0.082) | (0.025) | (0.173) |
| **Observations** | 25,031 | 73,979 | 46,010 | 3,916 | 146,134 | 6,767 |
| **N. Individuals** | 6,138 | 14,893 | 8,176 | 658 | 24,727 | 630 |

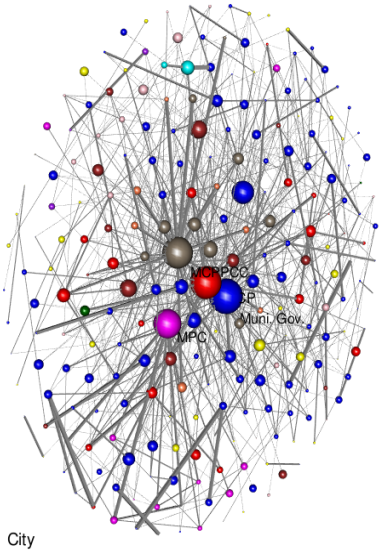
Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05

Note: Network and performance variables are standardized to be comparable in effect size. Annual growth rate is instrumented following the two-stage least square procedure.

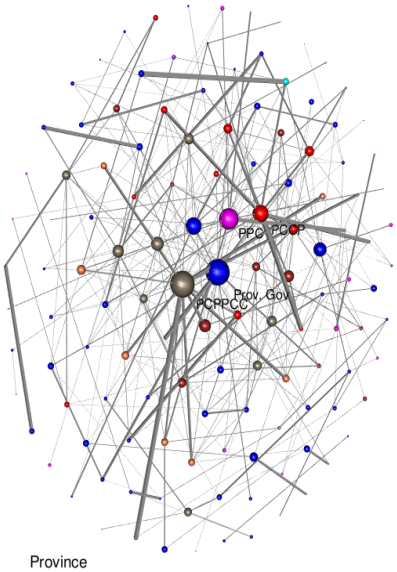
**Appendix 4. Visualization of Multiplex Organizational Networks**



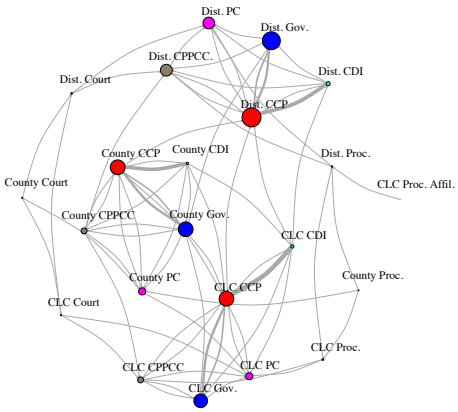

District & County

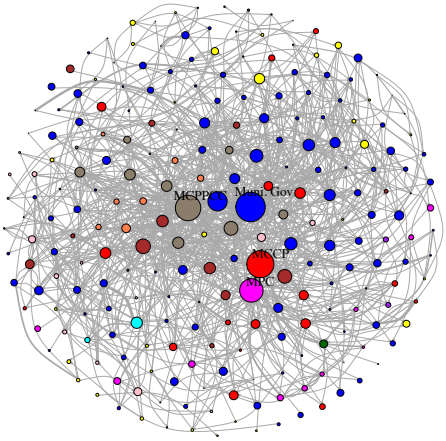


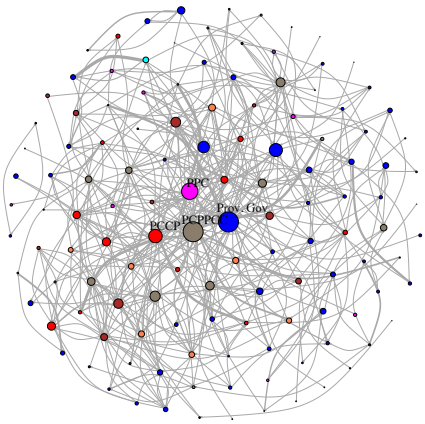

City




Province




CCP GOV LPC CPPCC MO CO CDI DP