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ABSTRACT

Effects of Social Networks on Job Attainment and Match Quality: Evidence from the China Labor-Force Dynamics Survey

Using nationally representative data from the 2012 and 2014 China Labor-force Dynamics Survey, this paper investigates the effects of network types (kinship/non-kinship) and network resources (information/influence) on job attainment and match quality in China. We find a wage premium obtained through both kinship and non- kinship networks but shorter job duration only in jobs obtained through non-kinship networks. In regards to the different types of networks, resources embedded in the networks are not important. This conundrum can be reconciled if we take the structure of the network and the type of work unit into account. Kinship networks are more pervasive in the public sector, with better earnings and stable job positions. Non-kinship networks bring about a wage premium but lead to job dissatisfaction, especially in regards to promotion opportunities. This paper highlights the structure of the job market when studying networks and sheds new light on the types of networks that really matter in job attainment and those that result in the possible loss of match quality.

JEL Classification: J30, J31, J64

Keywords: network types, network resources, job attainment, match quality

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1. Introduction

Social networks affect labor market outcomes worldwide and informal contacts via social networks have long been considered an important channel in the job seeking process (Granovetter, 1973; Granovetter, 2005). In developing countries like India, 45 percent of employees help a friend or relative land a job (Beaman and Magruder, 2012). Even in developed countries, where markets are more competitive, a large percentage of jobs are obtained through social networks, social networks accounting for some 30-60 percent of employees helping a friend or relative obtain a job in the US job market (Ioannides and Loury, 2004; Topa, 2011). One important role of networks is to diffuse information about job vacancies among potential job seekers. Job seekers are often informed of jobs through social networks. Subsequent behaviors such as whether the job seekers actually apply for the jobs and whether employers hire them remain unknown. In addition, the information channel formed by these social networks may not fully explain why firms employ a large proportion of their employees through such networks. At least three actors are involved in the process of job matching: employers, employees and intermediators. There is anecdotal evidence on the employer-side to elucidate possible mechanisms of the matching process and evaluate the effects on the quality of the match (Brown et al., 2016; Burk et al., 2015; Dustmann et al., 2016; Heath, 2018; Munshi, 2003). The role of social networks in job attainment has been partitioned into "information" and "influence" (Bian et al., 2015; Lin et al, 1981; Yakubovich, 2005). In the former, networks acting as intermediators between job seekers and employers, provide information. In the latter, networks use their influence to make referrals for job seekers, either by affecting employers' decision-making or by directly providing jobs. Although these two channels have been evaluated separately, their heterogeneous effects are understudied.

This paper uses nationally representative and longitudinal data from the China Labor-force Dynamics Survey (CLDS) to investigate the effects of the type of network (kinship/non-kinship) and network resources (information/influence) on job attainment and job match quality in China. We find there is a wage premium for jobs obtained via a network. After partitioning networks into kinship and non-kinship, we further present that the wage premium of kinship networks is similar to that of non-kinship networks but only those jobs obtained through non-kinship networks show a decline in job duration. Two key conundrums of these findings are worth highlighting. Why do the different types of networks lead to a similar wage premium but different job duration? As wage premium and job duration are two aspects of the quality of the match, why do higher wage premium and shorter job duration coexist in jobs obtained through non-kinship networks? This can be reconciled when we introduce the structure of the network and the type of work unit. Kinship networks are more pervasive in the public sector with higher earnings and stable positions. Non-kinship networks bring about a wage premium but lead to job dissatisfaction, especially in promotion opportunities. In regards to network types, we find that the effects of resources embedded in the network are not important. It is the type of network rather than the resources embedded in it that really matter in the process of job attainment in China. One possible explanation is that intermediators make a difference if they are kin, irrespective of the information they provide or the referrals they make. The kinship networks in China serve as examples of nepotism, especially in the public sector.

This paper contributes to the literature in three ways. First, we contribute to the literature on the effects of networks of different tie strengths (Bian, 1997; Gee et al., 2017a; 2017b; Granovetter, 1973; Yakubovich, 2005). Granovetter (1973) suggests that weak ties are more effective than strong ties since weak ties convey less redundant information. There is hardly a consensus of empirical evidence on this, however. Recent studies cast doubt on the merits of weak ties (see e.g. Centola, 2010; Christakis and Fowler, 2007). This paper provides new evidence on the effectiveness of networks with strong ties in China. After providing a picture of how various types of networks affect job attainment and match quality in different sectors, we highlight that the composition of the type of work unit matters when studying networks. Second, prior work confirms the role of networks in the process of job obtainment, acting as either information providers or influencers. However, except for the studies by Nordman and Pasquier-Doumer (2015) and Cappellari and Tatsiramos (2015), there is limited empirical evidence on the difference between them. In addition, the measurement of networks remains ambiguous (Dustmann et al., 2016; Gagliarducci and Manacorda, 2020; Hensvik and Skans, 2016; Kramarz and Skans, 2014). For example, if a worker enters an establishment where a former coworker is already employed, she is assumed to have acquired the job through a network (Hensvik and Skans, 2016). How networks affect the matching process is unclear. The effects of different resources embedded in the networks remain to be illuminated by exploiting *ad-hoc* survey data. We use CLDS's direct information on whether networks provide information or make referrals for job seekers. Our analysis deepens the understanding of networks in job attainment by separating the types of networks and the resources embedded in the networks. Third, although it is accepted that networks help a job seeker land a job quickly, the empirical evidence is mixed on the effects of networks on job match quality. We examine the effects of networks on different dimensions of match quality, including wages, job duration, job turnover intention, and nonpecuniary job satisfaction.

The remainder of the paper is structured as follows. Section 2 documents related literature. Section 3 describes the data and presents summary statistics. Section 4 outlines the empirical framework. Section 5 presents the results and Section 6 concludes.

2. Related Literature

2.1 Network types and job attainment

Since the seminal work by Granovetter (1973), a burgeoning body of literature has investigated the structure of networks. Networks are coarsely divided into strong (e.g. close friends, relatives, or family) and weak (e.g. acquaintances) according to emotional intensity, intimacy, and reciprocal services. Sociologists, however, use network classifications and characteristics that are more complex (Bian, 2018). Granovetter (1973) suggests that strong networks share information within ties whereas weak networks bridge individuals across communities. Weak networks are important in the job market since they broaden the information sets and bring new information that goes beyond strong networks. Boorman (1975) presumes that compared with weak ones, strong networks take more time to maintain. As compensation, information about job vacancies diffuses through strong networks in priority. Magruder (2010) finds that fathers (not mothers) serve as useful network connections to their sons' (not daughters') employment in South Africa. Kramarz and Skans (2014) show that young Swedish employees benefit from their parents in terms of shorter transitions into first jobs and better labor market outcomes. Nordman and Pasquier-Doumer (2015) investigate heterogeneous effects of different family networks (e.g. structure, strength, and embedded resources) and find that the strength and embedded resources rather than the size of the family network play key roles in job transitions, suggesting the importance of the quality of the network. Horváth (2014) and Cappellari and Tatsiramos (2015) suggest that the effects of network quality on job match quality depend on the degree of homophily (the tendency of individuals to befriend others who are similar to themselves). Higher homophily reduces mismatches.

2.2 Network resources and job attainment

Given that different types of social network have different embedded resources and provide different functions, some studies have investigated the association between job attainment and network resources. There are two key resources embedded in the labor market: information and influence. Most extant work does not differentiate between these two. For information networks, the most common view posits that it reduces search frictions (Ioannides and Loury, 2004; Topa, 2011). However, Bentolila et al. (2010) argue that job information obtained through social networks does not match with employees' productive advantage. Employees balance shorter unemployment duration through social networks with higher productivity via formal channels. The dispute on whether information improves or reduces match quality boils down to the quality of the social network. Horváth (2014) demonstrates that when employees' homophily with social networks is high, an information network provides better matches than a formal channel. Consequently, social networks increase the match efficiency of the job market despite favoritism. This rationale, however, may not coincide with the finding that low-skilled workers are more likely to obtain jobs through social networks (Brown et al., 2016; Kramarz and Skans, 2014).

To understand the functions and mechanisms of social networks, existing studies focus on the motivations of referrers and employers. For signal theories, high-ability workers are more likely to be tied with each other due to network inbreeding (Hensvik and Skans, 2016; Montgomery, 1991). Firms use parental quality as a signal of young quality (Kramarz and Skans, 2014). As regards screening and monitoring theories, Heath (2018) argues that firms use referrals to mitigate moral hazard problems rather than select unobservably good workers. The referral providers will be punished if recipients perform poorly, therefore, the recipients will exert effort. Firms use group liability to improve productivity. Pallais and Sands (2016)'s field experiment evidence shows that referred workers do not exert more effort to avoid letting their referrers down, which contradicts the screening and monitoring theories. Regarding learning theories, referrals provide more precise match quality than the external market (Brown et al., 2016; Dustmann et al., 2016). Compared to workers employed through formal channels, those who get their jobs through referrals initially obtain higher wages and are less likely to switch firms. These effects decline with tenure as workers' real productivity is gradually revealed. In terms of search cost theories, Burks et al. (2015) find that referred workers possess similar productivity to those employed through formal channels in the call center and trucking industries. Firms hire workers through referrals primarily because a lower labor turnover rate is observed among referred workers and lower recruitment costs are incurred. Regarding political dynastic theories, job attainment through social networks is based on rent-seeking activities or a *quid-pro-quo* exchange between employers and politicians, which may be more prevalent in developing countries or the public sector (Fafchamps and Labonne, 2017; Gagliarducci and Manacorda, 2020).

2.3 Social networks and job match quality

Prior work compares heterogenous effects of formal and informal contacts (like social networks) on various forms of job match quality such as job-seeking rate, wages, turnover rate, and job satisfaction. Bentolila et al. (2010) present that networks bring about declines in unemployment duration and wages in the US and Europe, implying that networks facilitate job seeking at the expense of production efficiency. Kramarz and Skans (2014) show that the prices of landing a job through networks are human capital mismatch and lower entry wages, while the benefits are shorter search time and higher productivity. Dustmann et al. (2016) and Burks et al. (2015) find that workers earn higher wages and are less likely to leave the firms if they obtain their jobs through referrals. Brown et al. (2016) reveal that referred candidates experience higher employment probability, longer tenure, and an initial wage advantage but all such effects diminish over time.

Two heuristic ideas can be summarized from the extant literature. First, the motivations of employees, employers, and intermediators all matter in the process of job matching through networks. As Kramarz and Skans (2014) underscore, more research is needed on employers' motivations to seek employees via network recruitment. Second, network resources are important aspects of networks, since these resources indicate how different types of networks really work. This paper highlights the structure of the labor market, which indirectly complements the role of employers. In addition, we attempt to disentangle the effects of network resources in the presence of network type.

3. Data and Sample Statistics

3.1 Data and study sample

The data used in this study are from the CLDS, administered by Sun Yat-Sen University, which is the first nationally representative and longitudinal labor-force survey in China. Using a rotating panel design, the CLDS has been administered every two years since 2012. The 2012 baseline wave of CLDS consists of a total of 16,253 individuals, of whom 43% are employees, 2% are employers, 13% are self-employed, and 42% are farmers. Our analytic sample is from the 2012 and 2014 CLDS[1]. Since we investigate the effects of networks on job attainment and match quality, we mainly focus on employees aged 18-64. After dropping observations without job-seeking channels and those with other missing data, we obtain a balanced panel comprised of 2,552

[1] The data is publicly available at http://css.sysu.edu.cn/.

observations.

3.2 Network types

Notable cross-cultural heterogeneities exist in network types (Fiori et al., 2008). For instance, a large proportion of US families may develop connections with their neighbors whilst people in Africa generally get support from their clans. In traditional Chinese society (especially in rural areas), networks are extended through the "overlapping of egocentric networks" in which the closeness of blood ties matters. Thus, we divide network types into kinship and non-kinship. The survey includes the question: "*What is the most important channel to obtain your (last/latest) job?*" with responses being (1) substitute parents, (2) substitute relatives, (3) internal recruitment, (4) from vocational institutions, (5) referral from relatives, (6) referral from classmates/friends, (7) referral from other acquaintances, (8) apply directly, (9) from the Internet, (10) job fair, (11) public recruitment test, (12) arranged by the government organizations, (13) votes. To identify whether jobs are obtained through informal (networks in our case) or formal channels, we construct a dummy variable (*Networks*)[2] equal to 1 if responses are (1), (2), (3), (5), (6) or (7) and 0 otherwise. To partition kinship and non-kinship networks, we redefine *Networks* as a categorical variable with a 3-point scale (1 = "(6)(7)", 2 = "(1)(2)(3)(5)", and 0 otherwise). Values of 0, 1, and 2 denote formal channels, non-kinship, and kinship networks, respectively. In our sample, 48.2% of jobs in China are obtained through networks, with 22.7% obtained from kinship networks and 25.5% obtained from non-kinship networks (see Table 1), which is similar to that of Beaman and Magruder (2012) for India.

3.3 Embedded resources

The CLDS provides us with a unique opportunity to capture resources embedded in the networks. We employ the question: "*Among those who provide help for your (last/latest) job attainment, what did they do specifically for you?"* with the responses of (1) provide job information, (2) provide information of firms/employers, (3) provide concrete suggestions for applications, (4) help prepare application materials, (5) prepare

[2] As the survey asks the most important channel to obtain the job, we do not distinguish job seekers who use formal and informal channels jointly (Xiong et al., 2017).

application materials in person, (6) help register and submit the application, (7) referral, (8) help connecting people who may be decisive in the job recruitment, (9) arrange visiting with people who may be decisive in the job recruitment, (10) help visiting people who may be decisive in the recruitment, (11) help solving concrete problems in application, and (12) provide the job directly. We define a dummy of information networks equal to 1 if responses are (1) - (6), 0 otherwise. We further generate a dummy of influence networks equal to 1 if responses are (7) - (12), and 0 otherwise. 32.5% of employees in our sample receive information and 23.5% receive influence.

3.4 Match quality

Following Cappellari and Tatsiramos (2015), we introduce wages, job duration and job satisfaction as proxies of job match quality. Wages are measured as annual and hourly wages in 2011 and 2013, with the 2011 wages adjusted to 2013. Job duration is defined as the tenure calculated according to the initial year of the last job. When analyzing the effects of networks on job duration, we use the 2014 CLDS to construct the flow sampling. The initial year of the (last/latest) job is recorded. Some employees quit their jobs before 2014, while others are still employed. Thus, our job duration measure may suffer from rightward censoring. We measure job satisfaction based on 10 job-related domains rated by the respondents, including (1) promotion opportunity, (2) utilization of ability/skills, (3) income, (4) whether others respect the work, (5) safety, (6) work time, (7) interest in the job, (8) satisfaction of the coworkers, (9) freedom to express their opinions, (10) overall job satisfaction. Each item is measured on a 5-point scale from 1 = very satisfactory to 5 = very unsatisfactory.

3.5 Control variables

We include variables for age, gender, tenure, tenure squared, type of work unit, marital status, education, father's education, *Hukou*, party membership, health status. To capture network quantity, the number of people who provide information or help when seeking a job and its squared term are also included. A detailed introduction of definitions of variables is available in Table 1.

[Table 1 About Here]

4. Empirical Framework

4.1 Networks and wages

We first estimate the effects of networks on wages. The main identification issue is that the error term might be correlated with networks due to the existence of unobservables. For instance, high-ability employees are more likely to use networks (homophily effects) to make fuller utilization of their abilities. Meanwhile, low-ability employees may tend to use their available networks to compensate for their inferiority in the labor market. Thus, omitted variables such as ability might be either positively or negatively correlated with networks in the job-seeking process, thereby resulting in overestimation or underestimation of the impacts of networks. As Kramarz and Skans (2014) and Brown et al. (2016) show, the low-skilled are more likely to obtain jobs through networks, which is also the case in the Chinese labor market (Xiong et al., 2017). The omitted variables are inclined to be negatively correlated with networks and lead to underestimated biases.

To alleviate potential biases due to omitted variables, we adopt fixed-effects (FE) estimation. The specific FE models are as follows.

$$\ln y_{it} = \alpha_0 + \alpha_1 Networks_{it} + X'_{it}\alpha_3 + \mu_i + \upsilon_t + \epsilon_{it} \quad (1)$$

$$\ln y_{it} = \beta_0 + \beta_1 Nonkinship_{it} + \beta_2 Kinship_{it} + X'_{it}\beta_3 + \mu_i + \upsilon_t + \varepsilon_{it} \quad (2)$$

where $\ln y_{it}$ is the translog wage of employee i at time t, $Networks_{it}$ is a dummy indicating whether a job is obtained through a network or not; X_{it} is a vector of individual and parental characteristics, μ_i and υ_t denote employees' and time fixed effects, respectively, and ϵ_{it} and ε_{it} are error terms. For equation 2, we replace $Networks_{it}$ with $Nonkinship_{it}$ and $Kinship_{it}$ to capture the idiosyncratic effects of different types of networks.

In addition, we attempt to identify possible heterogeneous effects of information and influence networks on wages:

$$\ln y_{it} = \gamma_0 + \gamma_1 Networks_{it} + \gamma_2 Information_{it} + \gamma_3 Influence_{it} + X'_{it}\gamma_4 + \mu_i + \upsilon_t + \vartheta_{it} \quad (3)$$

where $Information_{it}$ and $Influence_{it}$ represent information and influence networks of employee i at time t. Other specifications are the same as equation 1. Finally, if there exists a wage premium associated with networks, a natural question is whether higher network intensity brings about a higher wage premium. Bentolila et al. (2010) state that too much information may result in mismatches because there will be irrelative or redundant information. Hence, we introduce network quantity and its squared term in equation 3.

4.2 Networks and job duration

4.2.1 Hazard model

We introduce a hazard model to identify the effects of networks on job duration. Suppose j is a continuous length of job duration with the density and cumulative density function of $f(j|X)$ and $F(j|X)$ given time-invariant covariate X. The survivor function, $S(j|X)$, and the hazard function, $\lambda(j|X)$, is defined as follows:

$$S(j|X) \equiv 1 - F(j|X) = \mathrm{P}(T \geq j|X) \tag{4}$$

$$\lambda(j|X) = \lim_{h \downarrow 0} \frac{\mathrm{P}(j \leq T < j+h|T \geq j, X)}{h} = \lim_{h \downarrow 0} \frac{F(j+h|X) - F(j|X)}{h} \cdot \frac{1}{1-F(j|X)} = \frac{f(j|X)}{S(j|X)} \tag{5}$$

Then,

$$\lambda(j|X) = -\frac{dlnS(j|X)}{dj} \tag{6}$$

And $F(0|X) = 0$, if $\lambda(j|X)$ is given, we have

$$F(j|X) = 1 - \exp\left[-\int_0^j \lambda(j|X)\,ds\right] \tag{7}$$

$$f(j|X) = \lambda(j|X)\exp\left[-\int_0^j \lambda(j|X)\,ds\right],\ j \geq 0 \tag{8}$$

4.2.2 Maximum likelihood estimation with censored flow data

Assume T_i^* and C_i^* denote the true and censored job duration, respectively, of employee i. The observed job duration, j_i, is obtained as

$$j_i = \min(T_i^*, C_i^*) \tag{9}$$

Let d_i represent the censored indicator (1 if uncensored, 0 if right censored).

$$d_i = \mathbf{1}(T_i^* < C_i^*) \tag{10}$$

In our case, for those who quit their jobs before 2014, j_i is calculated as the job duration from the year that the job started to the year the job ended. We could observe the true job duration T_i^*. For those who are still employed in 2014, j_i is calculated as the job duration from the year the job started to 2014. We actually observe the censored duration C_i^*, which is smaller than the true job duration since the individuals are still employed. Thus, the censored indicator d_i will be 0 for those individuals.

The conditional likelihood function in translog form is expressed as follows:

$$\ln L = \sum_i \{d_i \ln f(j_i|X_i) + (1 - d_i)\ln S(j_i|X_i)\} \quad (11)$$

When the hazard function is given, $\ln f(j_i|X_i)$ and $\ln S(j_i|X_i)$ can be calculated using equations 4 and 5. We have applied different hazard function forms to guarantee the robustness of our results. First, we set the parametric hazards as exponential distribution ($\lambda(j|X_i) = \exp(\alpha + X_i'\beta)$), Weibull distribution ($\lambda(j|X_i) = \exp(X_i'\beta)\alpha j^{\alpha-1}$), and Gompertz distribution ($\lambda(j|X_i) = \exp(X_i'\beta)\exp(\alpha + \gamma j)$) Second, we run a semiparametric model of Cox estimation ($\lambda(j|X_i) = \lambda_0(j)\exp(X_i'\beta)$). Finally, to capture unobserved heterogeneities, we perform a mixed proportional hazard ($\lambda(j|X_i, v_i) = \lambda_0(j)\exp(X_i'\beta)\exp(\alpha + \gamma j)$) estimate.

5. Results

5.1 Networks and wages

Table 2 presents the results based on FE estimates of the effects of networks on wages. We show that employees who obtain a job through networks enjoy a 9.4% wage premium compared to those using formal channels (column 1). To avoid possible correlations between job-seeking channels and individual fixed effects, we rerun the estimates using the correlated random effect model developed by Mundlak (1978) (column 2) and the results are similar to that of column 1. To separate the effects of different network types, we introduce kinship and non-kinship networks (column 3) and find that the wage premium from kinship networks is slightly higher than that from non-kinship ones (9.7% vs. 9.1%). In columns 4 and 5, we examine possible heterogeneous effects of information and influence networks on wages. We observe non-significance in both information and influence networks, though both coefficients are positive. We then estimate the effects of network quantity by introducing this variable and its squared term. The results reveal that there exists an inverted "U" shape between network quantity and wages, meaning that the wage premium increases with the number of people who provide information or help, and then decreases beyond approximately 5 intermediators. If the wage premium is associated with longer work hours due to the network, the results would suffer from "spurious regression" since wages are measured annually. To rule out this possibility, we employ hourly wage as the dependent variable and rerun the estimation (column 7). The estimated coefficient remains significant and similar in quantity (8.8%).

[Table 2 About Here]

5.2 Networks and job duration

Next, we detect the effects of networks on job duration. Before regressions, we begin with graphical evidence. Figure 1 presents separate Kaplan-Meier survival curves for employees who obtain their jobs through networks and those who obtain them through formal channels. There is *prima facie* evidence that those who obtain jobs via networks are more likely to quit than are those drawing on formal channels. After dividing networks into kinship and non-kinship, Figure 2 shows that employees who obtained their jobs through non-kinship networks are most likely to quit their jobs. The estimated results are presented in Table 3. For columns 1-3, we specify parametric hazard functions to be exponential, Weibull, and Gompertz distribution, respectively. In column 4, we present a semiparametric model of the Cox estimation. Column 5 captures individual-level unobserved heterogeneity using a mixed proportional hazard function. We finally estimate the effects of networks on job duration as a continuous variable (columns 6 and 7), which is an inverse indicator of the hazard in columns 1-5. Surprisingly, we uniformly observe insignificant effects of networks on job duration, regardless of functional form. Such insignificant effects of networks on job duration may be attributable to the fact that we do not separate network types.

[Figure 1 About Here]

[Figure 2 About Here]

[Table 3 About Here]

Therefore, we examine the effects of different network types on job duration (see Table 4). We find that employees who obtained their jobs via non-kinship networks are about 23% more likely to quit their jobs than those using formal channels. However, relative to employees drawing on formal channels, landing jobs via kinship networks has no significant effects on job duration. Our results are quite robust due to using different functional forms of the hazard model. We also plot the survival likelihood regarding information (see Figure 3), which shows that the assumption is satisfied. After that, we check the effects of information and influence networks on job duration (see Table 5). The results demonstrate that information networks are slightly associated with a higher likelihood of quitting a job than influence networks, which is visualized in Figure 4.

[Table 4 About Here]

[Figure 3 About Here]

[Table 5 About Here]

[Figure 4 About Here]

5.3 Explanations

To summarize, for the effects of networks on wages, jobs obtained through networks are better paid than those obtained via formal channels. However, network resources, regardless of whether they are information or influence networks, do not affect job attainment. What matters is the type of network rather than embedded resources. For network quantity, the wage premium displays an inverted “U” shape in the number of intermediators in landing a job. The effects of networks on job duration are heterogeneous and the effects of network type dominate. Seeking a job via a non-kinship network is associated with shorter job duration.

Why do wage premium and job duration reduction coexist in the jobs obtained through the non-kinship network? Before answering this question, we attempt to clarify whether employees actively or passively quit their jobs. Although detailed firm-level data are unavailable, we introduce the type of work unit to capture the main determinant of job duration in China. To be specific, we divide the work unit into the public sector (including state-owned enterprises (SOEs) and government institutions) and the non-public sector. In China, the SOEs are dominant in the administratively monopolistic sectors with relatively stable positions and well-paid wages. We compare several key variables between the public sector and the non-public sector (see Table 6). Employees in the public sector have higher earnings, fewer work hours, longer job duration, and are more likely to obtain their jobs through kinship networks. Nonetheless, we cannot hastily conclude that the public sector pays more since their employees are also better educated. It will take much effort to prove these facts (Lu et al., 2012), which is beyond the scope of this paper. Before 1986, job positions in the public sector were administratively distributed rather than fairly competed for in the job market. Children whose parents worked in the public sector would take priority to be employed in the public sector, which is known as the institutions of substitution (*Dingti*) and internal recruitment (*Neizhao*) in the Chinese labor market (Bian, 1994). Although these unfair institutions have been officially canceled since 1986, children whose parents work in the public sector are still more likely to enter the public sector due to severe agent-principal problems in the public sector. Results from Table 7 confirm that jobs obtained through kinship rather than non-kinship networks are more likely to be prevalent in the public sector. These findings are in accordance with the wage premium in jobs obtained through kinship networks.

[Table 6 About Here]

[Table 7 About Here]

Since direct information on whether employees actively quit their jobs or not is unavailable, we exploit employees' labor turnover intention. The CLDS asks respondents: "*What is your plan on the job in the next two years?*" with the responses of (1) find another job or start a business, (2) keep the current job, (3) quit the job and take training, (4) quit the job for fertility, (5) attend training, (6) quit the job and take care of family, (7) retire, (8) maintain the current situation, and (9) quit for some time and then find a job. We keep responses (1)(2)(8), which account for 94% of all responses. We generate a dummy of labor turnover intention, equal to 1 if the respondent intends to find another job or start a business and 0 otherwise. Approximately 16.5% of employees are inclined to find another job in the next two years. We run FE estimates of how networks affect job turnover intention. Results in Table 8 show that employees who obtained their jobs via non-kinship networks are more prone to actively quit their jobs, which is consistent with the results from the hazard model in Table 5.

[Table 8 About Here]

We now confirm that the type of work unit is responsible for the reduction in job duration, especially for jobs obtained through non-kinship networks. Though having a wage premium, employees who obtain their jobs through non-kinship networks tend to quit. To account for the coexistence of wage premium and higher labor turnover intention for jobs obtained through non-kinship networks, we further detect how networks affect different domains of job satisfaction (see Table 9). Employees who obtained their jobs via non-kinship networks are less likely to be satisfied with their opportunities for promotion and increased income, though they are more prone to be satisfied with their coworkers. Additionally, those who obtained their jobs through kinship networks are less likely to be satisfied with their promotion opportunities, the utilization of their ability, and their freedom to express opinions, which are consistent with the characteristics of jobs in the public sector. With regards to network resources, influence networks are beneficial for most subdomains of job satisfaction. We also find that overall job satisfaction is higher for employees who obtained their jobs through influence networks.

[Table 9 About Here]

What kind of network really matters in landing a job? Our results recall the conventional classification of networks by tie strength (Boorman 1975; Granovetter, 1973). Reminiscent of Bian (1997), we emphasize strong networks. In regards to network type, resources embedded in the network may not be crucial. Our results imply that even though networks may make it easier for job seekers to obtain higher wages, they also cause job dissatisfaction in specific subdomains (e.g. promotion opportunity). One novelty of our results lies in the finding that job duration is linked with the type of work unit, which is associated with the utilization of various types of network.

6 Conclusion

This paper investigates the role of networks in job attainment and job match quality in China. We find a network-induced wage premium and heterogeneous network effects on job duration. There is a wage premium and shorter job duration in jobs obtained via non-kinship networks. In regards to the type of network, however, we do not find significant effects of resources embedded in networks. This can be reconciled when introducing network structure and type of work unit. Kinship networks are more pervasive in the public sector, with higher earnings and relatively stable positions. Non-kinship networks also provide a wage premium but lead to job dissatisfaction.

This paper provides insights into the role of networks in the process of obtaining jobs. Resources embedded in the networks are likely to result in heterogeneities in the quality of the job match. We are unable to detect significant heterogeneous effects between information and influence networks, however, it is indeed the network type that matters in job attainment and match quality. In China, where the network closeness is blood-based, jobs obtained through kinship networks possess both higher wages and longer job duration. Although prior work attempted to measure different functions of networks, the motivation of the intermediators to provide information or referrals for the employees are far from illuminated. The existent literature ignores the reciprocal nature of networks (Bian, 2018). Since non-kinship networks have weak motivation, the information they provide or the referrals they make may not make a huge difference. One key insight from our study is that when studying the networks the labor market matters. Additionally, although the networks provide a wage premium, they also lead to job dissatisfaction, especially in regards to promotion opportunity. As Chinese job seekers are more concerned with fringe benefits and workload when networks are mobilized, this paper responds to Xiong et al. (2017)'s call for future research on social networks and their impacts on better jobs with a special look at nonpecuniary domains (e.g. job freedom and promotion) rather than focusing only on wages.

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Tables and Figures

Table 1 Summary Statistics

Variables	Descriptions	Obs.	Mean	SD
ln*y*	Log of Annual wage (yuan, 2013 ppp)	2,552	10.197	0.729
Networks	Obtain job through networks (Kinship or Non-kinship)=1, Formal channels=0	2,552	0.482	0.500
	Formal channels=0,	2,552	0.518	/
Networks	Kinship	2,552	0.227	/
(Categorized)	Non-kinship	2,552	0.255	/
Information	Information=1, otherwise=0	2,552	0.325	0.468
Influence	Influence=1, otherwise=0	2,552	0.235	0.424
Age	Age	2,552	39.9	9.78
Gender	Male=0, female=1	2,552	0.454	0.498
Work Unit	Public sectors=1, Non-public sectors=0	2,552	0.414	0.493
Marriage	Married=1, unmarried=0	2,552	0.872	0.334
Education	Years of schooling (No school=0, primary school=6, middle school=9, high school=12, college=15, university=16, master=19, doctor=22)	2,552	10.970	3.902
Father's education	Years of father's schooling	2,552	7.317	3.485
Hukou	Urban=1, rural=0	2,552	0.470	0.499
Party membership	Yes=1, otherwise=0	2,552	0.181	0.385
Health status	Very healthy=1, health=2, general=3, unhealthy=4, very unhealthy=5	2,552	2.130	0.813
Networks quantity	No. of people providing information or help in landing the job	2,530	2.218	2.945
Hour	Working hours per year	2,535	2082.4	919.6
Turnover intension	Plan in the next two years (seeking for another job=1, no change=0)	6,964	0.165	0.371
Duration	Truncated duration of the job	6,764	9.04	7.89

Table 2 The Effects of Networks on Wages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Networks	0.094***	0.090***					0.088**
	(0.031)	(0.031)					(0.043)
Non-kinship			0.091**		0.085**		
			(0.040)		(0.041)		
Kinship			0.097***		0.093***		
			(0.034)		(0.034)		
Information				0.048	0.032		
				(0.035)	(0.034)		
Influence				0.045	0.017		
				(0.034)	(0.034)		
Networks quantity						0.029*	
						(0.016)	
Quantity squared						-0.003*	
						(0.002)	
Individual/Year FE	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES
N	2552	2552	2552	2552	2552	2530	2535
Adj. R^2	0.154	/	0.154	0.148	0.154	0.150	0.129

Notes: Column 2 is estimated by the correlated random effects developed by Mundlak (1978). For column 7, the dependent variable is hourly wage. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 3 The Effects of Networks on Job Duration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Networks	0.084	0.074	0.081	0.0967	0.082	-0.084	-0.080
	(0.062)	(0.063)	(0.062)	(0.0613)	(0.063)	(0.056)	(0.054)
Unit	-0.672***	-0.739***	-0.728***	-0.6909***	-0.731***	0.721***	0.668***
	(0.093)	(0.094)	(0.094)	(0.0934)	(0.097)	(0.080)	(0.079)
Education	-0.028***	-0.023**	-0.025***	-0.0296***	-0.026**	0.036***	0.028***
	(0.010)	(0.010)	(0.010)	(0.0097)	(0.010)	(0.009)	(0.009)
Age	-0.470***	-0.508***	-0.488***	-0.4425***	-0.490***	0.403***	0.423***
	(0.024)	(0.025)	(0.024)	(0.0245)	(0.027)	(0.024)	(0.023)
Age	0.006***	0.006***	0.006***	0.0052***	0.006***	-0.005***	-0.005***
squared	(0.000)	(0.000)	(0.000)	(0.0003)	(0.000)	(0.000)	(0.000)
Marriage	0.232**	0.226**	0.239**	0.2491**	0.239**	-0.054	-0.116
	(0.096)	(0.096)	(0.096)	(0.0990)	(0.097)	(0.085)	(0.083)
Gender	1.053***	1.088***	1.080***	1.0496***	1.084***	-0.890***	-0.919***
	(0.067)	(0.067)	(0.067)	(0.0662)	(0.071)	(0.059)	(0.058)
Father	-0.001	-0.001	-0.001	-0.0012	-0.001	-0.003	0.001
education	(0.011)	(0.011)	(0.011)	(0.0105)	(0.011)	(0.010)	(0.010)
Hukou	0.190**	0.188**	0.188**	0.1989**	0.189**	-0.139*	-0.141*
	(0.086)	(0.087)	(0.087)	(0.0895)	(0.087)	(0.076)	(0.074)
Party	-0.881***	-0.890***	-0.890***	-0.8771***	-0.890***	0.767***	0.695***
	(0.170)	(0.171)	(0.171)	(0.1613)	(0.171)	(0.132)	(0.134)
Health	0.184***	0.183***	0.184***	0.1898***	0.185***	-0.172***	-0.163***
	(0.035)	(0.035)	(0.035)	(0.0351)	(0.036)	(0.032)	(0.031)
Constant	4.485***	4.772***	4.704***	/	4.740***	-3.961***	-4.422***
	(0.505)	(0.506)	(0.507)	/	(0.554)	(0.490)	(0.460)
Province	YES	YES	YES	YES	YES	YES	YES
Scalars		ln *p*	*Gamma*		*Gamma*	ln *sig*	ln *gam*
		0.195***	0.031***		0.031***	0.340***	-0.316***
		(0.024)	(0.005)		(0.006)	(0.022)	(0.024)
					ln *the*		
					-4.014		
					(6.225)		
N	6764	6764	6764	6764	6764	6764	6764
L.L.	-3484.5	-3453.1	-3467.2	-8972.2	-3467.2	-3465.4	-3455.4

Notes: The mean and median exit time is 9 and 6 years, respectively. The observation of those who have exited the job market before 2014 is 1,177. The dependent variable is hazard ratio in columns 1-5 and job duration in columns 6-7. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 4 The Effects of Network Types on Job Duration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Non-kinship	0.222***	0.225***	0.232***	0.236***	0.235***	-0.210***	-0.206***
	(0.075)	(0.075)	(0.075)	(0.074)	(0.076)	(0.069)	(0.066)
Kinship	-0.024	-0.042	-0.035	-0.011	-0.035	0.015	0.017
	(0.072)	(0.072)	(0.072)	(0.071)	(0.073)	(0.065)	(0.062)
Controls	YES	YES	YES	YES	YES	YES	YES
Scalars		ln *p*	*Gamma*		*Gamma*	ln *sig*	ln *gam*
		0.197***	0.031***		0.032***	0.338***	-0.318***
		(0.024)	(0.005)		(0.006)	(0.022)	(0.024)
					ln *the*		
					-3.741		
					(4.374)		
N	6764	6764	6764	6764	6764	6764	6764
L.L.	-3479.6	-3447.3	-3461.4	-8967.2	-3461.4	-3460.7	-3450.2

Notes: Dependent variable is hazard ratio in columns 1-5 and job duration in columns 6-7. Robust standard errors in parentheses. *** p<0.01.

Table 5 The Effects of Embedded Resources on Job Duration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Non-kinship	0.196**	0.197**	0.203***	0.207***	0.207***	-0.174**	-0.176**
	(0.078)	(0.078)	(0.078)	(0.077)	(0.080)	(0.073)	(0.069)
Kinship	-0.040	-0.059	-0.053	-0.028	-0.052	0.039	0.037
	(0.074)	(0.075)	(0.075)	(0.073)	(0.075)	(0.068)	(0.065)
Information	0.102	0.113	0.114	0.110	0.118	-0.124*	-0.118*
	(0.071)	(0.071)	(0.071)	(0.069)	(0.072)	(0.065)	(0.062)
Influence	0.044	0.051	0.052	0.051	0.052	-0.065	-0.047
	(0.081)	(0.081)	(0.081)	(0.079)	(0.082)	(0.075)	(0.072)
Controls	YES	YES	YES	YES	YES	YES	YES
Scalars		ln *p*	*Gamma*		*Gamma*	ln *sig*	ln *gam*
		0.198***	0.032***		0.033***	0.337***	-0.320***
		(0.024)	(0.005)		(0.006)	(0.022)	(0.024)
					ln *the*		
					-3.257		
					(2.709)		
N	6764	6764	6764	6764	6764	6764	6764
L.L.	-3478.5	-3446.0	-3460.1	-8966.1	-3460.0	-3458.9	-3448.4

Notes: Dependent variable is hazard ratio in columns 1-5 and job duration in columns 6-7. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 6 Comparison of Key Variables Between Public and Non-public Sectors

	(1)	(2)	(3)	(4)
Sample	Full	Non-public	Public	Non-public - Public
Variables	sample	sectors	sectors	
ln *Annual wage*	10.066	9.938	10.334	-0.397***
(yuan)	(0.893)	(0.901)	(0.814)	(0.020)
ln *Hourly wage*	2.600	2.383	3.047	-0.665***
(yuan)	(1.120)	(1.103)	(1.020)	(0.024)
Annual working	2093	2237	1680	557***
hours (hours)	(1096)	(1145)	(810)	(22.6)
Duration	9.506	7.930	13.610	-5.680***
(year)	(8.222)	(7.348)	(8.930)	(0.191)
Kinship	0.565	0.516	0.736	-0.219***
	(0.496)	(0.500)	(0.441)	(0.012)
Edu	9.685	8.663	11.992	-3.328***
(year)	(4.195)	(4.013)	(3.646)	(0.062)

Notes: Standard errors in parentheses of the mean in columns 1-3, standard errors of the t-test in parentheses in column 4. *** p<0.01.

Table 7 The Effects of Networks on Types of Work Unit

	(1)	(2)	(3)	(4)
Networks	0.045***			
	(0.016)			
Non-kinship		0.019		0.020
		(0.020)		(0.020)
Kinship		0.064***		0.064***
		(0.017)		(0.018)
Information			0.012	0.006
			(0.018)	(0.018)
Influence			0.008	-0.003
			(0.020)	(0.020)
Controls	YES	YES	YES	YES
Individual/Year FE	YES	YES	YES	YES
N	2552	2552	2552	2552
Adj. R^2	0.011	0.014	0.004	0.014

Notes: Robust standard errors in parentheses. *** p<0.01.

Table 8 The Effects of Network Types and Embedded Resources on Labor Turnover Intension

	(1)	(2)	(3)	(4)
Networks	0.015			
	(0.015)			
Non-kinship		0.040**		0.040**
		(0.020)		(0.020)
Kinship		-0.002		-0.002
		(0.016)		(0.016)
Information			0.015	0.010
			(0.014)	(0.014)
Influence			0.002	-0.005
			(0.015)	(0.016)
Controls	YES	YES	YES	YES
Individual/Year FE	YES	YES	YES	YES
N	6964	6964	6964	6964
Adj./*Pseudo* R^2	0.039	0.040	0.039	0.040

Notes: Robust standard errors in parentheses. ** p<0.05.

Table 9 The Effects of Network Types and Embedded Resources on Different Domains of Job Satisfaction

	(1) *Prom.*	(2) *Abil.*	(3) *Inco.*	(4) *Resp.*	(5) *Safe*	(6) *Time*	(7) *Inte.*	(8) *Coop.*	(9) *Opin.*	(10) *Over.*
Part A										
Non-kinship	0.061*	-0.015	0.054*	-0.021	-0.031	-0.003	0.012	-0.053**	0.006	-0.019
	(0.035)	(0.023)	(0.028)	(0.022)	(0.024)	(0.027)	(0.028)	(0.023)	(0.027)	(0.022)
kinship	0.070**	0.042**	0.038	0.026	0.014	0.015	0.021	0.023	0.045**	0.022
	(0.029)	(0.021)	(0.025)	(0.020)	(0.022)	(0.023)	(0.025)	(0.021)	(0.023)	(0.020)
Part B										
Information	0.028	0.018	0.009	0.027	0.005	0.025	0.040	0.026	0.034	0.016
	(0.028)	(0.020)	(0.024)	(0.020)	(0.021)	(0.023)	(0.024)	(0.020)	(0.023)	(0.019)
Influence	0.031	-0.052**	-0.054**	-0.034	-0.015	-0.030	-0.040	-0.042*	0.003	-0.078***
	(0.033)	(0.023)	(0.027)	(0.022)	(0.024)	(0.026)	(0.027)	(0.023)	(0.026)	0.021)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	5377	7975	8640	8131	8559	8550	7827	7688	7347	8584

Notes: The dependent variables are (1) promotion opportunity, (2) utilization of ability and skills, (3) income, (4) whether others respect the work, (5) safety, (6) working time, (7) interest in the work, (8) satisfaction of coworkers, (9) freedom of expressing opinions and (10) overall job satisfaction. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Figures

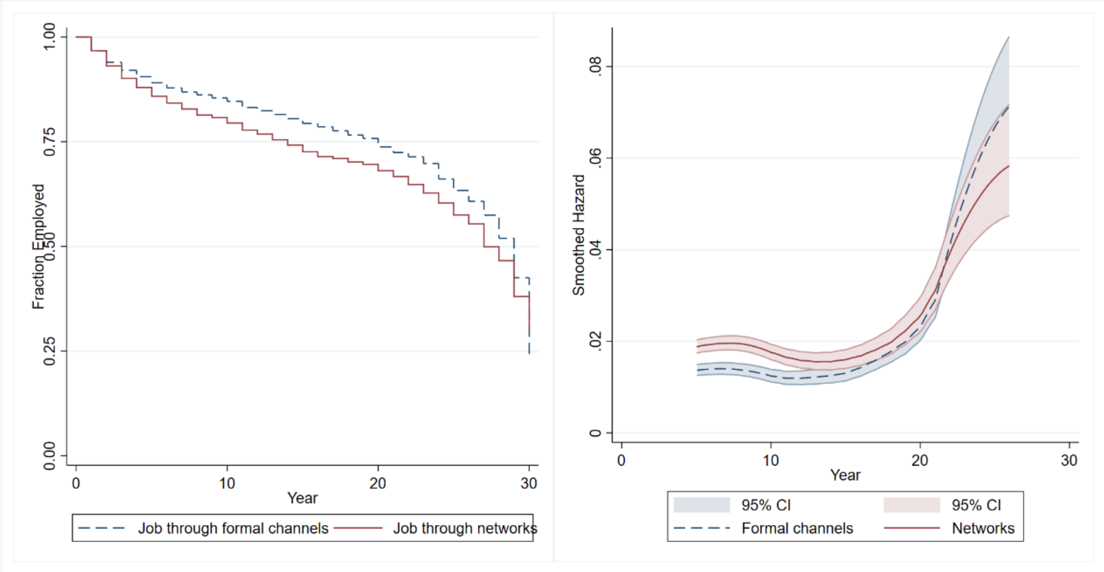

Figure 1 The Effect of Networks on Job Duration

Notes: Kaplan-Meier survival curves and smoothed hazard estimates are plotted for those who obtain jobs through networks and formal channels.

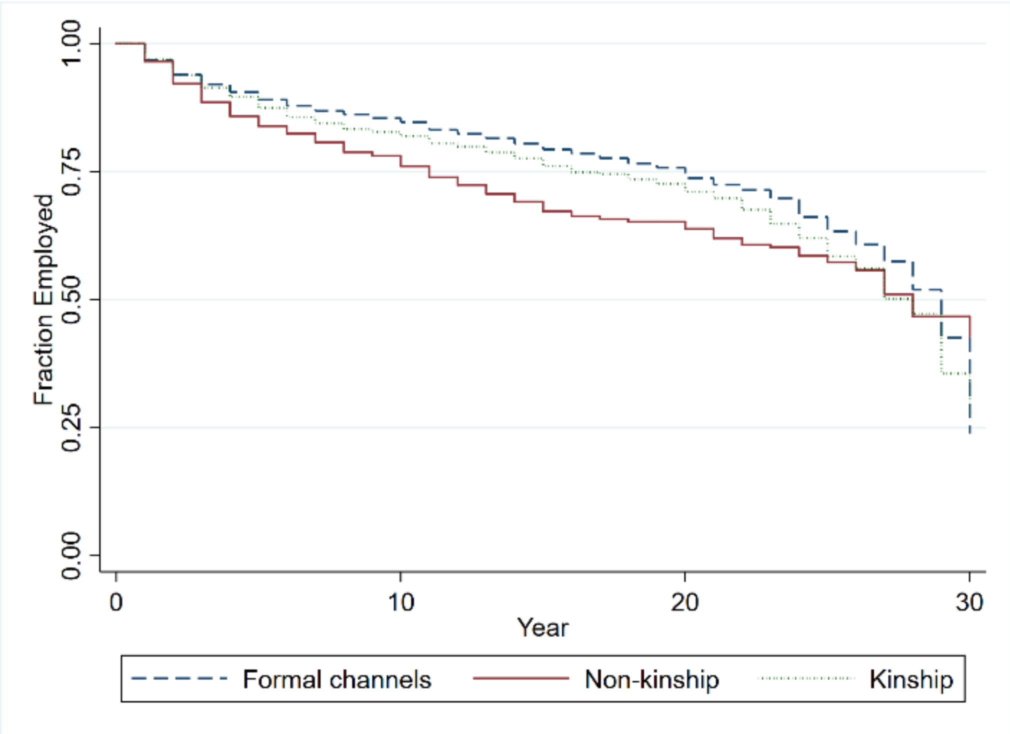

Figure 2 The Effect of Network Types on Job Duration

Notes: Kaplan-Meier survival curves are plotted for those who obtain jobs through Kinship, Non-kinship, and formal channels.

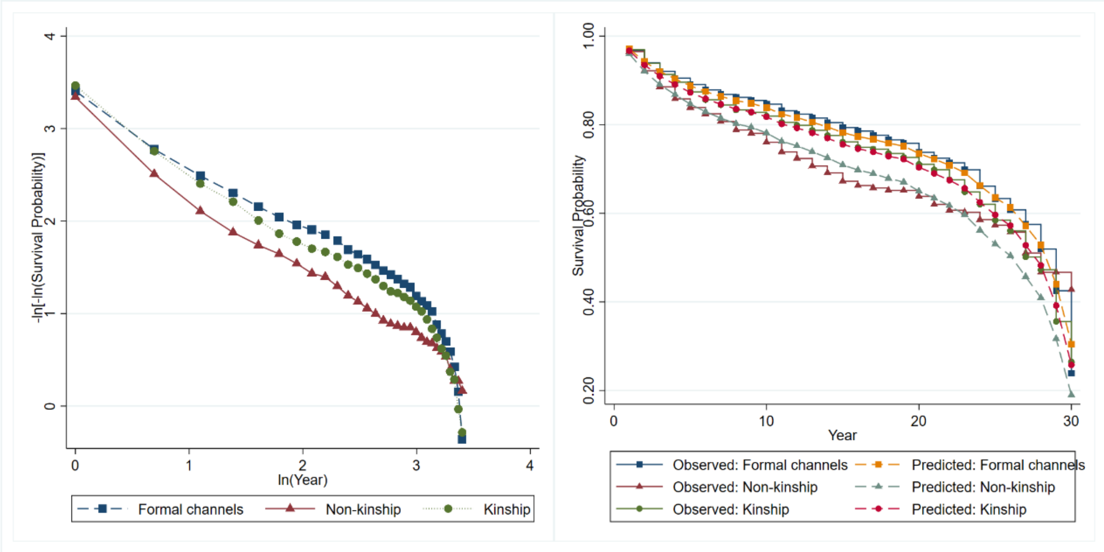

Figure 3 The Proportional Analysis and Fitting of the Network Types

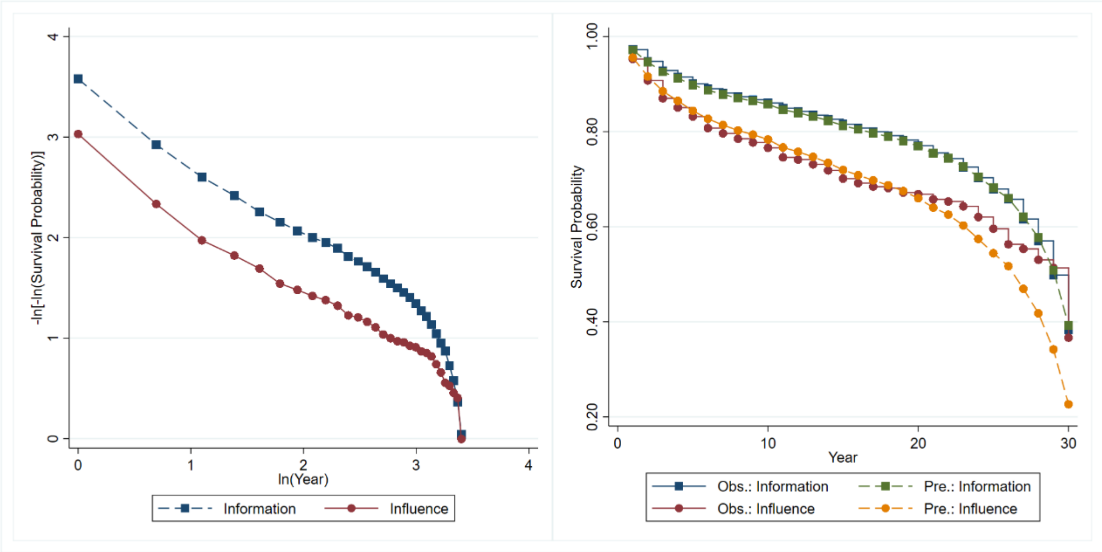

Figure 4 The Proportional Analysis and Fitting of the Network Resources