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Social Network of Urban Labor Force: Attributes and Measurement

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Abstract

Individuals connect with society through both emotional and obligatory relationships, as well as cooperative relationships rooted in the social division of labor. This study introduces the concepts of open and closed networks to capture these distinct relational pathways and characterizes social networks in terms of breadth, closeness, and trust. Using data from the 2012 China General Social Survey and a Confirmatory Factor Analysis (CFA) approach, we construct a comprehensive social network index for both open and closed networks. The results reveal that larger cities in China exhibit stronger open networks, whereas smaller cities are dominated by closed networks. Further empirical analysis of influencing factors supports these findings. These results align with China's stage of urbanization and provide new insights into social network dynamics in other transitional economies.

Keywords: Open network, Closed network, Structural equation model, City size

1. Introduction

Social networks serve as critical bridges between individuals and society, shaping how individuals access and utilize social resources (Granovetter, 1973). These networks influence the dissemination of employment opportunities and salary incentives, guiding labor force decisions on city choices and contributing to skill development (Burt, 1992). Typically, individuals connect with society through two distinct pathways: one involves close ties within familiar circles, such as relatives, classmates, and neighbors(Putnam, 2000); the other is based on broader societal identities, fostering connections through workplace relationships and professional partnerships(Fukuyama, 1996). This paper examines these pathways by introducing the concepts of closed and open networks and developing a comprehensive measurement index for social networks.

Closed networks are characterized by strong ties that provide stable social connections. These ties often facilitate job seekers in accessing repeated and homogeneous information, helping them secure desirable positions (Bian, 2009). In contrast, open networks rely on weak ties, which lack emotional support but offer diverse, non-redundant information(Granovetter,1973). Such networks promote individual development and innovation (Burt, 1991). The dominant forms of social interaction in cities evolve with urban growth. In smaller cities, social interactions are typically confined to specific geographic areas, forming networks rooted in kinship and locality. These networks are close-knit and stable, making closed connections particularly significant. As cities expand, residents increasingly interact with unfamiliar groups, and the division of labor becomes more complex. This shift fosters diverse social networks, particularly in workplaces, where relationships are more fluid and less emotionally grounded. At this stage, open networks play a pivotal role in the urban labor market.

1.1 Literature Review

Ties are fundamental elements that shape the structure of social networks. Granovetter (1973) introduced the classic theory of strong and weak ties, highlighting their role as vital bridges between individuals and society. He defined ties based on interaction frequency, emotional strength, intimacy, and reciprocal exchange. Building on this foundation, scholars have extensively debated the "importance" of strong and weak ties. Some researchers (Hansen, 1999; Marsden and Campbell, 1984; Levin and Cross, 2004) emphasize the role of weak ties as critical "bridges" linking economic and social phenomena with individual behavior (Granovetter, 1973). Lin (1986) further argued that weak ties not only facilitate information flow but also help individuals access social capital, such as power, wealth, and institutional resources.

Conversely, other scholars (Bian and Ang, 1997; Krackhardt, 2003) contend that strong ties are more influential. For example, Bian and Ang (1997), Chang (2011), and Chen et al. (2013) highlighted the importance of strong ties in China, where cultural norms prioritize familial and blood relationships, and government policies emphasize social harmony and employment stability. These factors render strong ties more significant in Chinese labor markets.

Existing classifications of social networks include strong and weak ties (Granovetter, 1973), informal networks based on emotional connections versus formal networks grounded in group identity (Bian and Ang, 1997; Pichler and Wallace, 2008), superior-subordinate relationships among colleagues (Law et al., 2000; Han and Altman, 2008), and peer networks (Biggio and Cortese, 2013). However, these relational perspectives primarily frame social networks as forms of social capital, often overlooking their critical role in the labor market. Moreover, they fail to investigate the structural characteristics of social networks and their relationship to city size and urban development.

Empirical approaches to measuring social networks generally fall into two categories. The first involves using population proportions to assess network strength. Examples include the number of relatives and friends within a family (Knight and Yueh, 2008), the ratio of shared family surnames (Hsu, 1963), or the proportion of immigrant populations (Pedersen, 2008). The second approach dissects social networks into multidimensional indicators. Granovetter (1985), for instance, evaluates individual networks based on interaction frequency, emotional strength, intimacy, and reciprocity. Wheaton (1982) incorporates dimensions such as network density, complexity, and centrality, while Lin (2001) uses measures like reach, heterogeneity, and extensiveness to assess social capital. Bian (2017) employs meal-sharing behaviors, such as inviting others to meals, being invited, and dining together, as indicators of dinner party networks.

While these methods provide valuable insights, both have notable limitations. Approaches relying on population proportions often fail to capture the structural characteristics of networks, offering only a partial view of social interactions. In contrast, multidimensional indicator-based methods, while more detailed, have yet to produce a comprehensive measure that can consistently serve as an independent variable in empirical studies. These gaps highlight the need for a more integrated framework to analyze social networks in the context of labor markets and urban development.

1.2 Aims and Significance

This paper aims to investigate the structural characteristics of social networks through three dimensions: breadth, closeness, and trust. Utilizing data from the 2012 China General Social Survey, we employ Confirmatory Factor Analysis (CFA) to construct comprehensive indices for open and closed networks, enabling a systematic understanding of these two distinct social structures.

In the context of China's transitioning economy, the urban labor force's social networks exhibit a dual nature. Open networks, characterized by diversity and weak ties, dominate in large cities, while closed networks, shaped by close-knit, trust-based relationships, are more prevalent in smaller cities. These networks reflect a hybrid of cultural norms that prioritize familial ties and market-driven forces that facilitate diverse connections. Exploring the spatial distribution and defining characteristics of these networks offers a novel perspective on urban social dynamics in transitioning economies.

This study contributes to the literature by integrating the structural characteristics of social networks with the developmental stages of cities, providing a framework to interpret urbanization through the lens of open and closed networks. By employing structural equation modeling, we address the limitations of existing methods that often fail to capture both network indicators and structural features simultaneously. Finally, through an empirical examination of Chinese urban labor force networks, this paper reveals the correlation between city size and social network type, shedding light on the broader patterns of urbanization in developing countries.

2. Connotation of Dual Network and Hypotheses

2.1 Closed Network

Closed networks represent a key pathway for individuals to connect with society, particularly in the early stages of urban development. Their defining characteristics include:

Scale stability. Closed networks predominantly consist of relatives, classmates, and neighbors, with a fixed member size over a period. Relatives are inherent to family structures, with their number determined by family size. Classmates are formed during schooling, and their number remains static post-graduation. Neighbors are geographically proximate individuals within a residential area, and their number depends on the location of residence.

Structural redundancy. Relationships in closed networks are stable, close-knit, and characterized by highly homogeneous information, creating a familiar and steady environment conducive to emotional support and resource retention (Lee et al., 2005). This redundancy makes closed networks inherently exclusive, limiting the incorporation of new members. Structurally, they are dense and interconnected, with every individual linked to all nodes, resulting in an absence of structural holes and a high degree of redundancy.

Relationship formation. Closed networks are formed through emotional bonds and obligations. Resource flow is fixed, with those in higher economic or social positions typically serving as resource providers and those in lower positions as recipients. These networks provide emotional support and facilitate incremental improvements in individuals' economic and social status.

2.2 Open Network

In modern, market-based societies, familial production modes are declining, and social interactions no longer rely on traditional relationships. Individuals increasingly depend on open networks to access diverse social resources. Key characteristics of open networks include:

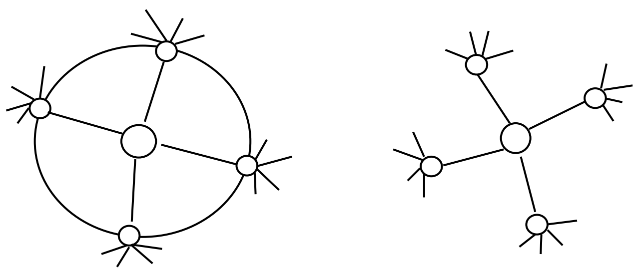
Scale stability. Unlike closed networks, open networks are formed through professional and societal integration. Membership transcends kinship, blood ties, and geographic constraints, with greater fluidity among members. The size and strength of these networks are influenced by occupational diversity; exposure to a broader range of professions enriches available resources. Consequently, open networks are dynamic and ever-changing.

Structural redundancy. Open networks are characterized by high mobility, non-redundant ties, and diverse relationships, enabling efficient information exchange. They are inclusive and open, with sparse structures marked by independent connections, numerous structural holes, and low redundancy. Central individuals in these networks hold informational and resource control advantages.

Relationship formation. In open networks, relationships are built on cooperation, reciprocity, and trust in institutionalized social norms. Resource transfer prioritizes efficiency and mutual benefit, following principles of market transactions, organizational protocols, and public ethics. Members of open networks often assume multiple roles across various groups, and the breadth of their participation strengthens the network's overall capacity.

Table 1. Social network characteristics

	Closed networks	Open networks
Scale Stability	Stable	Dynamics
Structural redundancy	Non-Redundancy	Redundancy
Relationship formation	Emotion	Social norms



A. Closed networks B. Open networks

Figure 1. Schematic Representation of The Social Network Structure

2.3 City Size and Social Network Distribution

Closed and open networks coexist within urban settings, functioning either as two relatively independent social systems or as dual attributes of the urban labor force's social networks. These networks serve distinct roles in the labor market. Closed networks foster a "peer effect" that primarily influences residential and employment choices. For instance, Araujo et al. (2010) found that the peer choices of Mexican immigrants significantly shaped their employment location decisions, an effect that persisted even when controlling for other social networks. This influence is amplified by information exchange within the network. Emotional support in closed networks encourages members to settle near one another, jointly expanding the network's scale in new locations.

Conversely, open networks facilitate "knowledge spillovers," enabling mutual learning among members to unlock potential productivity. High-efficiency workers can collaborate effectively, while low-efficiency workers improve their skills under the pressure of high-performing peers--a dynamic also described as the "peer effect" (Sacerdote, 2001; Falk, 2006). Large agglomerations of skilled labor in cities create opportunities for learning and innovation, enhancing overall labor productivity (Audretsch & Feldman, 2015; Moretti, 2009).

As urbanization progresses, the relative prominence of closed and open networks evolves:

In Smaller Cities. During the early stages of urban development, cities are small, urbanization rates are low, and the family remains the primary unit of social production. Social interactions are defined by proximity and intimacy, emphasizing personal relationships. Communication is restricted to a limited geographic area, with network members predominantly comprising kin and geographically proximate acquaintances. These relationships are stable and closely-knit. In this context, open networks are relatively underdeveloped and cannot effectively facilitate knowledge spillovers or access to advanced social resources. Consequently, closed networks dominate social interactions during this phase.

In Larger Cities. As cities expand and populations grow, social interactions diversify. The increasing complexity of the social division of labor enables greater collaboration and mutual benefit among strangers, fostering social networks formed within modern settings like workplaces. These networks, characterized by dynamic and flexible relationships, are composed of heterogeneous groups. Closed networks, constrained by homogeneity of information, struggle to provide transformative social resources. Open networks, by contrast, become vital for improving individual productivity and fostering innovation, which are necessary to meet the demands of highly specialized labor markets. Thus, in larger cities, social networks are predominantly structured around open networks.

From this analysis, the following theoretical hypothesis is proposed:

Hypothesis 1: The larger the city, the higher the level of individual open networks; the smaller the city, the higher the level of individual closed networks.

3. Data and Methods

3.1 Data

This study utilizes data from the Chinese General Social Survey (CGSS), initiated in 2003 as China's first national, comprehensive, and continuous academic survey project. The CGSS is conducted by the Survey and Data Center of Renmin University of China. For this analysis, the CGSS 2012 database was selected, encompassing data from 134 municipal districts (counties) across 28 provinces, cities, and autonomous regions, with a total of 11,765 valid responses. The questionnaire includes a main module (individual and family basic information) and thematic modules such as social networks, social capital, social donations, volunteer services, family roles, and urban culture. Due to differences in sample sizes between modules, this study retains only overlapping samples and excludes records with missing data. The final dataset comprises 5,350 individuals across 88 cities.

3.2 Construction of Social Network Comprehensive Index

This study constructs a social network index based on three dimensions of relationships within social networks: breadth, closeness, and trust. These dimensions reflect the ways in which social connections are established and maintained, as summarized in Table 2.

Breadth: The size of network nodes indicates the number of social relationships an individual has. A larger network allows access to more diverse and valuable information. For closed networks, the question "How many members of your family or relatives who do not live with you do you typically communicate with in a day?" is selected. For open networks, the "Number of individuals participating in political, leisure, recreational, and other group organizations" is used.

Closeness: Interaction frequency determines the strength and intimacy of connections between network members. For closed networks, "Frequency of meetings with relatives and friends who do not live together" is chosen. For open networks, "Frequency of going out to eat with other people" is selected.

Trust: Trust reflects the willingness of individuals to rely on one another and share resources. Mayer et al. (1995) define trust as "the willingness of a party to be vulnerable," while Ostrom et al. (1994) emphasize its role in ensuring adherence to group norms, thereby enhancing resource transmission efficiency. For closed networks, the question "How much do you trust your relatives?" is used. For open networks, "How much do you trust your coworkers?" is chosen.

Table 2. Social network dimension selection

Network Category	Dimension	Questionnaire
Closed network	Breadth	How many members of your family or relatives who do not live with you do you typically communicate with in a day?
	Closeness	Frequency of meetings with relatives and friends who do not live together (1 = daily; 5 = never).
	Trust	How much do you trust your relatives? (1 = least trusting; 4 = most trusting).
Open Network	Breadth	Number of individuals participating in political, leisure, recreational, and other group organizations.
	Closeness	Apart from family and relatives, how often do you go out to eat with other people (at least three outsiders at a time)? (1 = never; 5 = very often).
	Trust	How much do you trust your coworkers? (1 = least trusting; 4 = most trusting).

3.3 The Structural Equation Modeling (SEM) of Social Networks

Building on the preceding analyses, this study evaluates Chinese social networks using three common indicators for both open networks and closed networks: scale of ties, degree of connection, and trust. These indicators align closely with the respective network types. To empirically test the relationship between social networks (open or closed) and city size, this study employs Structural Equation Modeling (SEM) Derived from a path analysis put forward by Shipley (2000), SEM is now employed to analyze the causal effect for unobserved variables, which consist of observable variables, latent variables, and residuals(Hair et al., 2021;Sarstedt et al., 2022)..As a subset of SEM, Confirmatory Factor Analysis (CFA) is particularly well-suited for investigating relationships between multiple observable and latent variables. By identifying the relevant variables beforehand, CFA enables precise testing of these relationships and the path coefficients are estimated by AMOS software (Lowry& Gaskin,2014).Consequently, SEM is applied in this study to explore the proposed theoretical hypotheses, as outlined in Figure 2.

The model's assumptions are as follows:

(1). There are two distinct types of social networks, represented by the two exogenous latent variables: closed network and open network.

(2). The observable variables for closed and open networks are scale of nodes, tie strengths, and degree of trust.

(3). All subordinate and superior variables exhibit a positive relationship.

(4). Error terms are independent of the observable variables.

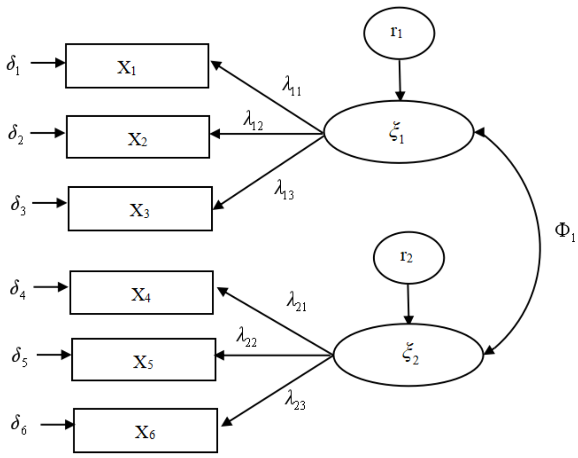


Figure 2. Path Diagrams Of Open And Closed Networks

In Figure 2, X1 to X6 represent the indicators of social networks, with closed networks and open networks illustrated as latent variables. Mathematically, the relationship is expressed as:

$$x = \Lambda_x \xi + \delta \tag{1}$$

where Λ_x is the factor loadings matrix, which quantify the strength of influence between latent variable ξ_j and observable variable x_i . A larger the coefficient indicates a stronger influence, while the coefficient Φ_1 captures the relationship between open network and closed network.

3.4 The Empirical Model of Influencing Factors

This paper examines the factors influencing dual social networks from three perspectives: individual, family, and city. Based on these dimensions, the following measurement model is established:

$$network_i = \alpha_0 + \beta_1 X_{individual} + \beta_2 X_{family} + \beta_3 X_{city} + \varepsilon_i \tag{4}$$

Where $network_i$ represents the dependent variables derived from the social network measurement indices described earlier, and ϵ denotes the error term.

The individual-level control variables include gender, age, work experience (and its square), whether the individual is a native of the area, and whether they have sought help during the job-hunting process (denoted as help).

At the family level, the variables include family income (denoted as home_in), father's education level (denoted as edu_f), and the occupational economic and social status index (denoted as edu_ISEI).

At the city level, the control variables include city size (denoted as pop), the proportion of the tertiary industry in GDP (denoted as structure), per capita paved road area (denoted as road), and the proportion of foreign enterprises (denoted as fdi).

All data for these variables are sourced from the CGSS 2012 and the China Urban Statistical Yearbook 2013. This model enables a comprehensive exploration of how various individual, family, and city-level factors influence the structure and distribution of social networks.

4. Results

4.1 Fitting Results

The model comprises 6 observable variables, 21 data points, and 14 parameters for estimation, meeting the conditions for model identification. As shown in Table 3, the modified model fit test statistics meet the adaptation standards, indicating that the theoretical model aligns well with the sample data and has high credibility.

Table 3. Goodness-of-fit of SEM

Goodness-of-fit	Test statistics(modified)	Critical Value
Absolute fit indices	GFI=0.983	0.5<NFI<1, better close to 1
	AGFI=0.956	0.5<IFI<1, better close to 1
	RMSEA=0.079	0.05<RMSEA<0.08 acceptable RMSEA<0 good
Comparative fit indices	NFI=0.926	0.5<NFI<1, better close to 1
	IFI=0.928	0.5<IFI<1, better close to 1
	CFI=0.928	0.5<CFI<1, better close to 1

4.2 Estimation Results of CFA

The estimation results are illustrated in Figure 3. Open networks and closed networks show a strong correlation, with a coefficient of 0.94.

For closed networks in China, the standardized path coefficients for breadth, closeness, and trust are 0.48, 0.58, and 0.10, respectively. The frequency of meetings with relatives and friends has the greatest impact, followed by number of occupations, and degree of trust. More frequent interactions with relatives provide individuals with better access to ideal social resources. In contrast, the degree of peer trust plays a more significant role in open networks, with a coefficient of 0.83. The coefficients for breadth and closeness are 0.16 and 0.19, respectively, indicating that while both dimensions are important in open networks, trust is the most influential factor. Due to the absence of kinship and blood ties, open networks rely more on trust between individuals to maintain relationships, whereas closed networks depend more on communication with relatives.

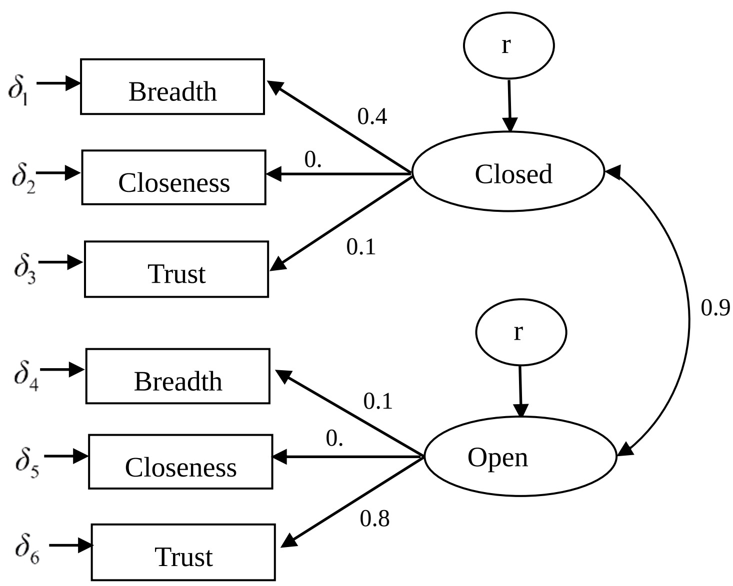


Figure 3. Estimation Results of Open And Closed Networks

The standardized path coefficients of the SEM are used to calculate the social network index. First, the range of all evaluation indicators is unified and converted into a 1-5 scale. Second, the path coefficients for the two types of social network observation variables are normalized. Lastly, the weighted sum of the closed network and open network indices is obtained, as shown in formulas (2) and (3).:

$$Index_i - close = 0.414 \times X_1 + 0.500 \times X_2 + 0.086 \times X_3 \qquad (2)$$

$$Index_i - open = 0.136 \times X_4 + 0.161 \times X_5 + 0.703 \times X_6 \qquad (3)$$

Formulas (2) and (3) are used to calculate the closed-network and open-network indices for the samples. Descriptive statistics for these indices, categorized by the three network types, are presented in Table 3. The relationship between urban size and the open network contrasts with that of the closed network when considering the mean values. On average, the closed-network index is highest in small and medium-sized cities and lowest in super-large cities, which is the opposite pattern observed for the open network.

Table 3. Descriptive statistics of open networks and closed networks

Index	City type	Sample size	Mean	S.D.	Min	Max
Closed networks	Type I（pop>500）	1,134	2.792	0.493	1.311	4.622
	Type II（100<pop<500）	1,612	2.995	0.520	1.2	4.822
	Type III（pop<100）	2,415	2.998	0.497	1	4.822
Open network	Type I（pop>500）	1,134	2.188	0.481	1	4.931
	Type II（100<pop<500）	1,612	2.106	0.463	1	4.696
	Type III（pop<100）	2,415	2.030	0.414	1	4.279

4.3 City Size and Social Network Index

The relationship between urban size and indices of Chinese social networks is further illustrated through scatterplots in Figures 4 and 5.

For closed networks, Figure 4 displays a downward-sloping trend, indicating a negative correlation between closed networks and city size. Megacities such as Beijing, Shanghai, and Guangzhou occupy the lower-right corner, while small to medium-sized cities like Huadian, Heihe, and Baicheng are predominantly in the upper-right corner. Conversely, Figure 5 reveals an upward-sloping trend for open networks, suggesting a positive correlation with city size. In this case, megacities such as Shenzhen and Shanghai appear in the upper-right corner, while small to medium-sized cities cluster in the lower-left, showing a distribution pattern opposite to that in Figure 4.

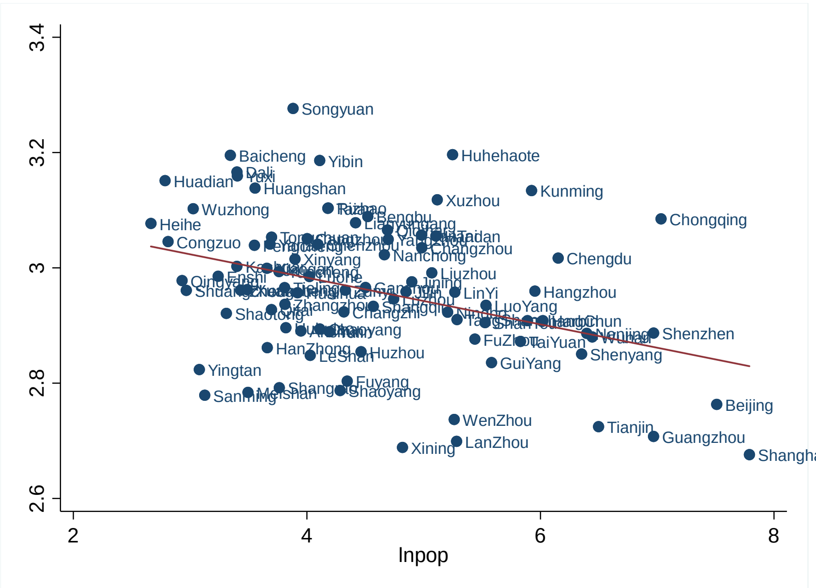


Figure 4. The Relationship Between The City Size And The Close-Network Index

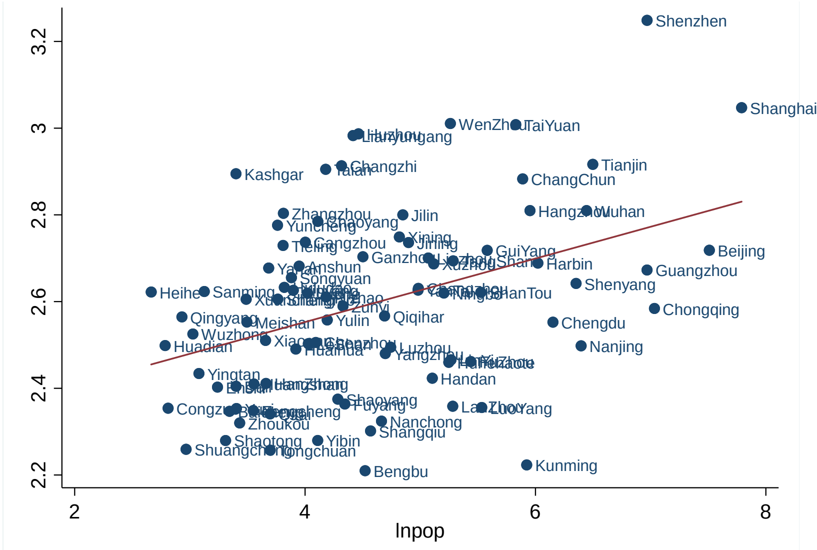


Figure 5. The relationship between the city size and the open-network index

Table 5 reports the estimation results of Equation (4). Columns (1)–(3) focus on closed networks, while columns (4)–(6) address open networks. For closed networks, gender has no significant effect, but age exhibits a significant negative impact. Work experience follows a U-shaped relationship with closed networks. Higher household income strengthens closed networks, whereas a father's ISEI score and education level are negatively associated with them. At the city level, larger populations and higher foreign investment reduce closed networks, while road density has a positive effect. For open networks, work experience demonstrates an inverted U-shaped pattern. Long-term local residence and reliance on personal connections during job searches show no significant impact. However, household income, along with a father's ISEI score and education level, positively influence open networks. At the urban level, larger populations promote open networks, whereas a higher proportion of the tertiary sector weakens them.

Table 5. Estimation results of social network influencing factors

	(1) fengbi1	(2) fengbi2	(3) fengbi3	(4) kaifang1	(5) kaifang2	(6) kaifang3
2.gender	-0.0008	-0.0036	0.0018	-0.0504***	-0.0578***	-0.0557***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
old	-0.0000	-0.0008***	-0.0007***	-0.0029***	-0.0016***	-0.0016***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
work_ex	-0.0026***	-0.0027***	-0.0021***	0.0060***	0.0029***	0.0033***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
work2	0.0000**	0.0000***	0.0000**	-0.0001***	-0.0000*	-0.0000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
native	0.0231***	0.0301***	0.0263***	-0.0239***	-0.0103	-0.0093
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
help	0.0150**	0.0146*	0.0144*	0.0139	0.0079	0.0080
	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
home_in		0.0000	0.0000**		0.0000***	0.0000***
		(0.000)	(0.000)		(0.000)	(0.000)
edu_f		-0.0060***	-0.0046**		0.0142***	0.0146***
		(0.002)	(0.002)		(0.002)	(0.002)
isei_f		-0.0004*	-0.0004*		0.0026***	0.0028***
		(0.000)	(0.000)		(0.000)	(0.000)
lnpop			-0.0130***			0.0168***
			(0.004)			(0.004)
road			0.0011*			0.0011
			(0.001)			(0.001)
fdi			-0.0449**			-0.0332
			(0.020)			(0.022)
structure			-0.0003			-0.0018***
			(0.000)			(0.000)
_cons	1.0767***	1.1392***	1.1949***	0.8534***	0.6645***	0.6396***
	(0.014)	(0.018)	(0.022)	(0.014)	(0.019)	(0.023)
N	3896	3203	3079	3896	3203	3079
r2	0.0154	0.0308	0.0502	0.1048	0.2146	0.2238

5. Discussion

The scatterplots highlight that larger cities tend to foster open networks, while smaller cities rely more on closed networks. High population mobility in megacities promotes trust-based interactions and reduces dependence on localized, closed networks. Economies of scale further enhance broad-based connections, making open networks dominant in large urban centers. In contrast, smaller cities, with limited populations, depend on close, localized ties rooted in personal relationships, obligations, and geographic proximity, where closed networks play a central role.

At the individual level, factors such as local residency, seeking help during job searches, and higher household wealth strengthen closed networks. Urban infrastructure also contributes by facilitating frequent interpersonal interactions. However, as city size increases and openness grows, closed networks weaken, reflecting the broader transition of social structures during urbanization. In smaller cities, geographic constraints and tighter social circles sustain these networks, while larger cities offer diverse resources that reduce reliance on close personal ties.

Economic affluence and higher paternal education expand access to broader social resources, promoting open networks. Large cities, with abundant employment opportunities enabled by economies of scale, further facilitate integration into open networks. However, the reliance on face-to-face interactions within advanced service sectors may sometimes limit the growth of open networks.

In conclusion, larger cities encourage open networks through greater resources and mobility, while smaller cities strengthen closed networks by relying on localized connections. These findings align with Figures 4 and 5, as well as Table 5, and reinforce the theoretical framework.

The dynamics of population concentration reveal that large cities, with their high mobility, foster labor agglomeration, which weakens traditional closed networks. In contrast, smaller cities, limited by geography and slower economic growth, experience delayed social transitions, with residents continuing to depend on familial and friendship ties.

The framework of open and closed networks presented in this study sheds light on uneven urban development in developing countries. It underscores how large cities serve as hubs for social and economic integration, while smaller cities remain anchored in localized, tight-knit connections, reflecting different stages of urbanization.

6. Conclusion and Limitations

This study proposes a novel classification of social networks into open and closed types, based on individual interaction patterns and social connections. It characterizes networks through three dimensions: breadth, closeness, and trust. Using confirmatory factor analysis (CFA) within a structural equation model, a comprehensive social network index was constructed and employed as an independent variable in empirical analysis.

Drawing on data from the 2012 China CGSS survey, the findings indicate that larger cities foster higher levels of individual open networks, while smaller cities are associated with stronger closed networks. These results align with China's urbanization trajectory and support the theoretical framework.

In terms of determinants, individuals with lifelong local residency or those who rely on personal connections for job searches are more likely to maintain strong closed networks. However, larger urban populations and greater city openness weaken these networks. Conversely, open networks benefit from factors such as family wealth, higher paternal education levels, and residence in larger cities, which provide broader opportunities and resources for social connection.

Despite its contributions, this study has several limitations: (i) Some indicators used to construct the network index may be incomplete. For instance, the "breadth" of open networks is measured by group participation, which might not fully capture the diversity of an individual's social interactions. (ii) The relatively small sample size limits the generalizability of the aggregated social network index at the city level. Expanding the sample with additional public survey data could improve representativeness. (iii)The study examines social networks at a single point in time, neglecting dynamic changes. Future research could incorporate longitudinal data to explore temporal shifts in network structures.

In conclusion, this study provides a new perspective on the relationship between urbanization and social networks by distinguishing between open and closed networks. While larger cities enhance open networks through greater opportunities and resources, smaller cities rely on the stability of closed networks rooted in localized connections. Addressing the identified limitations in future research could deepen our understanding of these dynamics and enhance the robustness of the findings.

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Authors' contributions

Prof. Xu Guo drafted the manuscript and Yueqi Han revised it. Shuai Zhao and Mengya Wu was responsible for data collection. All authors read and approved the final manuscript.

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Competing interests

Not applicable

Informed consent

Obtained.

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The Publication Ethics Committee of the Redfame Publishing.

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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