Econ 7217 Economic Analysis of Social Networks
Regression with Network Data

Chih-Sheng Hsieh

Department of Economics
National Taiwan University

February 26, 2024

Review of literature

- In this lecture, we will discuss different interpretations of network variables in regressions.
- In different contents, network statistics are used as explanatory variables to capture effects of
  - popularity or social capital (Mihaly, 2009; Conti et al., 2013; Fletcher, 2014; Lavy and Sand, 2016; Ho, 2016; Ferris et al., 2017);
  - information access or dissemination (Fleming et al., 2007; Schilling and Phelps, 2007; Hochberg et al., 2007; Tucker, 2008; Stephen and Toubia, 2010; Trusov et al., 2010; Banerjee et al., 2013; Bajo et al., 2016; Banerjee et al., 2013; Cappellari and Tatsiramos, 2015);
  - link dependence (Chinazzi et al., 2013; Minoiu et al., 2015);
  - individual effort (Calvó-Armengol et al., 2009);
  - certification and monitoring (Ding et al., 2017);
  - externality (Hsieh and Lin, 2018)

Review of literature

- Jackson et al. (2017) provide a survey on the economic consequences of the structure of social networks in Economics.
- Phelps et al. (2012) provides a survey on how networks influence knowledge creation, diffusion, absorption, and use in management science.
- There is also a large body of finance literature studying social network effects, such as Bajo et al. (2016) which studies underwriter networks; Huang et al. (2014) study board connections with investment banks and M&A transitions; El-Khatib et al. (2015) study CEO networks and merger performance; Engelberg et al. (2012) study how interpersonal connections between firm managers and bankers facilitate loan provision, etc.

Number of links as a measure of popularity (Mihaly, 2009)

- Mihaly (2009) studies whether "more friends mean better grades?"
- Data is from National Longitudinal Study of Adolescent Youth (Add Health), which contains detailed information on a sample of over 90,000 high school students in U.S. Every student in the study nominates up to five male and five female friends.
- She specifies the regression $Y_i = X_i\beta + \delta C_i + \epsilon_i$, where C_i are different centralities which capture popularity.
- The results show that GPA will increase if a person receives additional friendship nominations when treating the popularity measure C_i as exogenous.

Number of links as a measure of popularity (Mihaly, 2009)

- However, after dealing with the endogeneity of C_i by the instrumental variable approach (the instruments are the interactions of individual characteristics X_i with the mean of the corresponding characteristic in the grade by gender), the IV result shows that having more friends has a negative impact on academic performance.
- She explains that the negative effect of time constraints outweighs the positive impact of information sharing in the relationship between popularity and academic outcomes.

Number of links as a measure of popularity (Conti et al., 2013)

- In Conti et al. (2013), they ask two questions: what makes a student popular among high-school peers? And what are the economic gains from popularity later in life?
- They use the survey data of high school friendship relations of respondents from Wisconsin Longitudinal Study (WLS) to answer these two questions.
- They find evidence that the early family environment, school composition and school size play a significant role in shaping friendship networks.

Number of links as a measure of popularity (Conti et al., 2013)

- They find no effect from out-degree. But in-degree (popularity) has a positive effect on each individual's level of earnings some 35 years later.
- They deal with the technical problem of missing links (only one-third of each school population was sampled) by a pseudo-likelihood-based approach (for jointly modeling the number of friends in adolescent and the earning in adulthood).
- Their study points out the importance of early development of social skills alongside cognitive and productive skills as a basis for economic success in adult life.

Number of links as a measure of social capital (Ho, 2016)

- In Ho (2016), he studies the effect of an individual's number of friends on own health outcomes.
- He uses the Add Health data and exploits the panel structure of the friendship data to control individual fixed effects, and then uses the fixed effect estimates as the control function for the endogeneity problem on friendship nomination.
- He finds that having a larger number of friends improves physical and mental health and also lowers the frequency of smoking cigarettes.

Number of links as a measure of social capital (Ho, 2016)

Table IV. Estimation results

	Right hand side variable: number of friends			
Dependent variable	(1)	(2)	(3)	Observation
General health	0.027***	0.028***	0.066***	12,870
	(0.004)	(0.004)	(0.007)	
Overweight	−0.010**	−0.011**	−0.021***	13,146
	(0.004)	(0.005)	(0.005)	
Obesity	−0.008**	−0.008**	−0.017***	13,146
	(0.004)	(0.004)	(0.006)	
Sad	−0.011***	−0.011***	−0.018***	13,448
	(0.003)	(0.003)	(0.005)	
Depressed	−0.010***	−0.010***	−0.018***	13,447
	(0.004)	(0.004)	(0.006)	
Smoking	−0.016***	−0.020***	−0.057***	13,378
	(0.005)	(0.005)	(0.009)	
Estimated individual effects			√	
School fixed effects		√	√	
Individual covariates	√	√	√	
Parental covariates	√	√	√	
Neighborhood covariates	√	√	√	
Missing-variable dummies	√	√	√	

Robust standard errors clustered by schools in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Number of links to promote innovations (Fleming et al., 2007; Schilling and Phelps, 2007)

- Fleming et al. (2007) and Schilling and Phelps (2007) empirically estimate the network structural effects on individual and firm innovations.
- In Fleming et al. (2007), they look at the U.S. patent data between 1975 and 2002 and identify individual inventors of patents and their coauthors. They define regional networks based on Metropolitan Statistical Areas.
- They do not find evidence of small-world structure (cohesive clusters connected by occasional non-local ties) enhances innovative productivity.
- But they find out (1) shorter path length and (2) larger connected components correlated with an increase in subsequent patenting.

Number of links to promote innovations (Fleming et al., 2007; Schilling and Phelps, 2007)

- In Schilling and Phelps (2007), they construct a large, unbalance panel of U.S. firms from 11 high-technology manufacturing industries between 1990 to 2000. They build the alliance network among these firms using the Thomson Corp's SDC Platinum database. They study the relationship between "patent" (count of successful applications) and various firm level and industry level network measures, such as clustering, average path lengths, and centralities.
- They find firms embedded in alliance networks that exhibit both high clustering and short average path lengths will have greater innovative output than firms in networks that do not exhibit these characteristics.

Number of links as a measure of information dissemination (Stephen and Toubia, 2010)

- In Stephen and Toubia (2010), they study how the network in a large online social commerce marketplace generates values.
- Social commerce is similar to social shopping. While social shopping (like online word-of-mouth, e.g., Yelp.com) connects customers, social commerce connects sellers – each seller has his or her own online shop and there are hyperlinks connecting to others' shops.
- They use a company data that runs popular and rapid growing social commerce marketplaces in France, Germany, UK, and US and find that the network's value lies primarily in making shops more accessible to customers browsing the marketplace.
- The sellers that benefit the most from the network are those whose accessbility is most enhanced by the network.

Number of links as a measure of information extraction and dissemination (Bajo et al., 2016)

- In Bajo et al. (2016), they study how the network position of a lead initial public offering (IPO) underwriter in its network of investment banks affect various IPO outcomes.
- They form network links among investment banks using the record of IPO underwriting syndicates.
- The network plays two potential roles. Information dissemination – lead underwriter use the network to disseminate information about various aspects of the IPO firm to institutional investors. Information extraction – lead underwriter extracts useful information in pricing the IPO firm equity from institutional investors.

Number of links as a measure of information extraction and dissemination (Bajo et al., 2016)

- Their hypotheses are
  1. a more central underwriters can attract more attention from a larger number of institutions to the firm it takes public.
  2. a more central underwriter can more efficiently extract information about the valuation of the IPO firm from its connected institutions.
- They find more central lead IPO underwriters are associated with larger absolute values of offer price revisions, greater IPO valuations, larger IPO initial returns, etc.

Number of links as a measure of link dependence (Minoiu et al., 2015)

- The global financial crisis has underscored the role of financial connectedness as a potential source of systemic risk and macroeconomic instability.
- Minoiu et al. (2015) study the question whether financial interconnectedness can serve as an early warning indicator of crises.
- They establish the global banking network with the annual data on cross-border banking system exposures from the BIS (Bank for International Settlements) locational statistics over 1978 –- 2010.
- They find that increases in a country's own connectedness and decreases in its neighbours' connectedness are associated with a higher probability of banking crises after controlling for macroeconomic fundamentals.

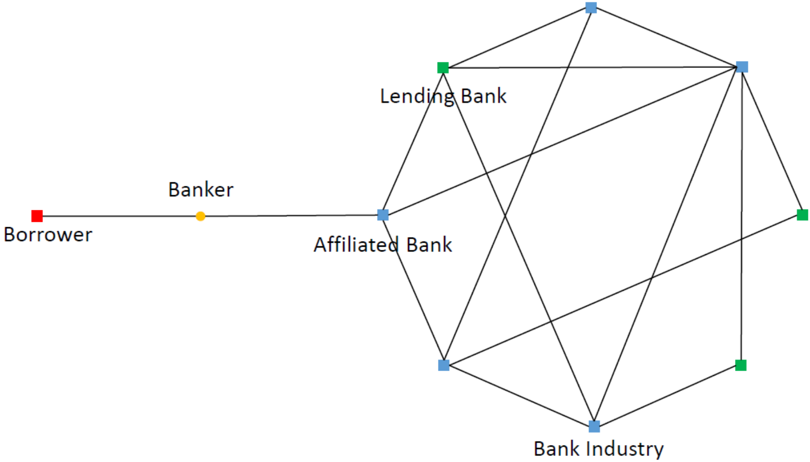
Number of links as a measure of individual effort (Calvo-Armengol et al., 2009)

- In Ballester et al. (2006) and Calvó-Armengol et al. (2009), they build a theoretical model to study the structural property of friendship networks on individual outcomes.
- They show that, at the Nash equilibrium, the outcome of each individual embedded in network is proportional to her Katz-Bonacich centrality measure.
- Calvó-Armengol et al. (2009) bring the theoretical prediction to the empirical Add Health data and show that the individual's position in a network is a key determinant of her studying performance.

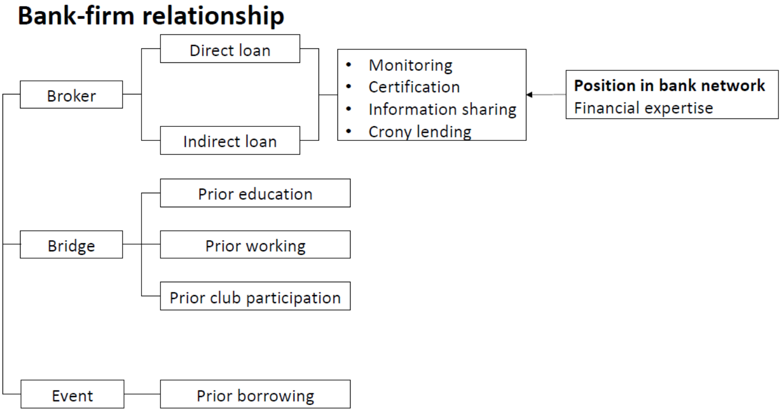
Number of links as a measure of certification (Ding et al., 2017)

- In Ding, Du, Hsieh, and Hu (2017), we study the Role of Commercial Bankers in Non-financial Corporations"
- Commercial bankers (executives, executive directors or non-executive/independent directors in banks) often serve as executive directors, non-executive directors or corporate executives in non-financial corporations.
- Thus, overlapping directors or executives can serve as the linkage between the borrowing firm and the commercial banking industry.
- We examine whether these bankers facilitate corporate borrowing with their connections to the banking industry.

Number of links as a measure of certification (Ding et al., 2017)

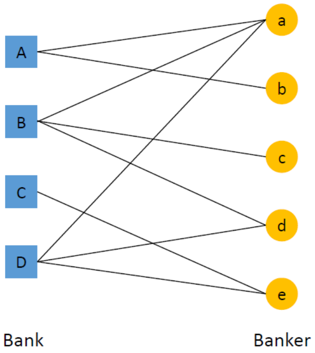


Number of links as a measure of certification (Ding et al., 2017)



Number of links as a measure of certification (Ding et al., 2017)

Connection Network



- Two mode network captures the duality nature of working affiliations.
- Here is an illustration of two mode network.
- It contains two different types of node sets, banks in the left column and persons in the right column.
- Bank A and director a are connected if a works in bank A. We only define connection between the banks and persons.
- We do not define connection within banks or directors.
- The reason is that such connection is raised automatically from two mode network.

Number of links as a measure of certification (Ding et al., 2017)

Data

Variable description

Variable Name	Description
Loan Size	Log loan size in US dollars 2013
Spread	Log loan spread
Banker Centrality	Summation of banker's two mode degree centrality
Affiliated Bank Centrality	Summation of affiliated bank's two mode degree centrality
Finexp	Dummy indicating that borrower firm has at least one financial expert banker
Firm Size	Log total book assets of the borrowing firm
TobinQ	Market value of firm's assets over the book value of assets
ROA	Return on assets ratio
Leverage	Long-term debt plus debt in current liabilities, divided by long-term debt plus debt in current liabilities plus stockholders' equity
Maturity	Months to maturity of the facility
Senior	Dummy that the debt has a priority over other debt obligations of the company
Syndicated	Dummy indicating whether the loan comes from a syndicate of banks
Bridge	Number of bridge connection between the borrower and the lenders
Lend History	Dummy indicating whether the borrower has borrowed a loan from at least one of the lenders before
Lending Bank Centrality	Summation of lending bank's two mode degree centrality
Direct Loan	Dummy indicating the borrower and at least one of the lenders share the at least one same banker
Short-distance Loan	Dummy indicating the shortest connection distance between the borrower and the lender is one or two

Number of links as a measure of certification (Ding et al., 2017)

Baseline Results

Full sample regression

	(1) Loan Size	(2) Loan Size	(3) Spread	(4) Spread
Banker Centrality	0.059***		-0.020***	
	(0.007)		(0.003)	
Affiliated Bank Centrality		0.055***		-0.022***
		(0.007)		(0.004)
Finexp	-0.125*	-0.020	0.017	-0.024
	(0.073)	(0.072)	(0.045)	(0.046)
Firm Size	0.346***	0.354***	-0.197***	-0.198***
	(0.039)	(0.040)	(0.015)	(0.015)
TobinQ	0.116***	0.113***	-0.265***	-0.264***
	(0.039)	(0.040)	(0.028)	(0.028)
ROA	0.967***	1.092***	-1.279***	-1.318***
	(0.359)	(0.380)	(0.286)	(0.289)
Leverage	0.095	0.035	0.798***	0.811***
	(0.164)	(0.167)	(0.094)	(0.096)
Maturity	-0.001	-0.001	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Senior	3.680***	3.751***	-1.154***	-1.201***
	(0.633)	(0.628)	(0.170)	(0.176)
Syndicated	3.243***	3.332***	-0.112	-0.142
	(0.500)	(0.498)	(0.152)	(0.153)
Industry Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
N	4621	4621	3733	3733
adj. R^2	0.478	0.463	0.524	0.522

Number of links as a measure of certification (Ding et al., 2017)

Tackling Endogeneity

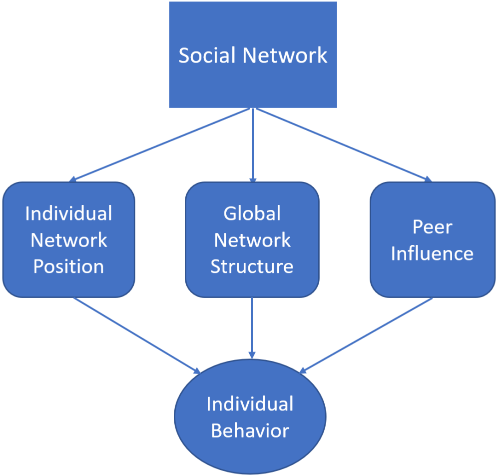
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Use centrality three years ago				Exclude bankers joining the borrower within three years				Use number of local banks as IV for centrality			
	Loan Size	Loan Size	Spread	Spread	Loan Size	Loan Size	Spread	Spread	Loan Size	Loan Size	Spread	Spread
Banker Centrality	0.067***		-0.016***		0.070***		-0.018***		0.237***		-0.058*	
	(0.010)		(0.006)		(0.010)		(0.006)		(0.066)		(0.031)	
Afflicted Bank Centrality		0.064***		-0.018***		0.067***		-0.018***		0.265***		-0.072*
		(0.009)		(0.005)		(0.009)		(0.006)		(0.084)		(0.039)
Controls and fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2976	2976	2333	2333	2976	2976	2333	2333	4621	4621	3733	3733
adj. R^2	0.532	0.529	0.518	0.520	0.533	0.529	0.520	0.519	0.119	0.141	0.469	0.459

- Three years prior to the start of the loan, banker's centrality should be unrelated to future loan decisions.
- If a banker is appointed to the borrowing firm in return for the loan, the deal is likely to take place shortly after the appointment.
- In a state with a larger number of local banks, a firm is more likely to hire a director from the commercial bank industry, hence having a larger centrality measure. But a borrower firm's geographical location is unrelated to the loan outcome, because the firm is unlikely to change its headquarter.

Motivation

- Social scientists generally agree that individual behaviors are shaped by their social networks. However, there are not necessarily common agreements on how specific network structures affect individual behavior.
- There is a debate on whether network closure (Coleman, 1988) or network brokerage (structural hole) (Burt, 1992) is more effective in facilitating information diffusion and adoption of new behaviors. While that followers of the two camps continue to propose new evidences, the debate seems never ending.
- In spite of many theoretical studies on economic consequences of social network structure (see a survey in Jackson et al., 2017), there are very few empirical investigations.
- Motivated from the unresolved debate and the lack of empirical results, we propose a comprehensive modeling approach to study network structural effects and demonstrate its usefulness in three network datasets.

Model


Social Network
Individual Network Position
Global Network Structure
Peer Influence
Individual Behavior

Model

- We adopt the Spatial Autoregressive (SAR) model

$$y_{i,g}^* = \lambda \sum_{j \neq i}^{m_g} \frac{w_{ij,g}}{\sum_{j \neq i}^{m_g} w_{ij,g}} y_{j,g}^* + x_{i,g}\beta_1 + \sum_{j \neq i}^{m_g} \frac{w_{ij,g}}{\sum_{j \neq i}^{m_g} w_{ij,g}} x_{j,g}\beta_2 + \alpha_g + \epsilon_{i,g}, \qquad (1)$$

  where $w_{ij,g} = w_{ji,g} = 1$ if agent i links to agent j and zero otherwise. $w_{ii,g} = 1$ a priori.
- we extend the above SAR model by incorporating local (from ego's perspective) and global network effects:
  - individual network measures, including degree centrality, eigenvector centrality, and clustering coefficient, are included in individual's characteristics $x_{i,g}$.
  - we specify $S_g = (S_{1,g}, \cdots, S_{L,g})'$, with each $S_{l,g}$ denoting a network structural measure such as the average degree, global clustering coefficient, etc., and replace α_g in (1) by $\alpha_0 + S_g\rho + \nu_g$, where ν_g is a new group-specific error that is uncorrelated with all of the other regressors.

Model

- One further extension considers that global network structures also moderate the peer influence in each network.
- We specify a random coefficient on the endogenous peer effect: $\lambda_g = \zeta_1 + S_g\zeta_2 + \xi_g$, where ζ_1 denotes a baseline effect and ζ_2 stands for a $L \times 1$ vector of coefficients which reflect how global network structures strengthen (or weaken) the magnitude of endogenous peer effects. ξ_g denotes a random normal disturbance with a mean zero and variance σ_ξ^2.
- The model that we propose to capture the network effects on individual behavior can be presented as:

$$Y_g^* = (\zeta_1 + S_g\zeta_2 + \xi_g)\widetilde{W}_g Y_g^* + X_g\beta_1 + \widetilde{W}_g X_g \beta_2 + \ell_g(\alpha_0 + S_g\rho + \nu_g) + \epsilon_g \quad (2)$$

- When behavioral outcomes are binary, we consider the spatial probit model.

$$y_{i,g} = \begin{cases} 1 & \text{if } \; y_{i,g}^* > 0 \\ 0 & \text{otherwise,} \end{cases} \quad (3)$$

Global Network Structural Effects

Average degree and variance of degree:

- higher average degree implies higher network density, which is helpful for network diffusion or social learning.
- the network will increasingly resemble a "hub-and-spoke" structure when the variance of degree gets higher. In this case, high-degree nodes become more influential and can trigger stronger peer influences.

Spectral properties (maximum and minimum eigenvalues):

- Moore and Newman (2000) studied percolation on an arbitrary finite sequence of dense network graphs and showed that there is a sharp threshold determined by the inverse of the maximum eigenvalue.
- Bramoullé et al. (2014) proposed a game theoretical model on networks and show that the minimum eigenvalue determines the responsiveness of agents acting relative to others' behaviors exhibited in the network.

Global Network Structural Effects

Number and size of network components:

- When all nodes belong to the same component, it is possible for information or behavior to spread from any node to any other node, given enough time.
- On the other hand, for many small components, information or behavior initiated from one component can not spread to nodes in other components.

Diameter and average path length:

- The distance between nodes plays a role indicating the speed of learning or diffusion, the efficiency of exchange and trade, and the accuracy of communicating information.

Global Network Structural Effects

Global clustering coefficient:

- There are both positive and negative implications of global clustering coefficient (transitivity) on network diffusions, as debated by Coleman (1988) and Burt (2002).

Assortativity and Homophily index:

- Under a positive assortativity, highly connected nodes more likely to be connected to other high-degree nodes, a kind of segregation pattern.
- As homophily increases, the propensity for a diffusion within a particular group rises, sometimes at the expense of the speed and extent of diffusion throughout the entire population.

Network Data Sets

AddHealth school networks:

- The Add Health longitudinal survey is a national representative survey of adolescents in grade 7 through 12 from 132 schools in US.
- AddHealth provides detailed information on respondents' demographic backgrounds, academic performance, health-related behaviors, and most importantly, friendship networks constructed from the respondents' nominations.
- We select 75 schools with the size between 50 and 400 from the Addhealth data for our analysis.
- We study three student outcomes – GPA, smoking frequency, and number of clubs participated.

Network Data Sets

Indian village networks:

- The Indian rural village survey was conducted in 2006, accompanied by an introduction of microfinance service provided by Bharatha Swamukti Samsthe (BSS) in rural southern Karnataka, India (Banerjee et al., 2013).
- There are 75 villages. In each village, a subset of villagers participated in answering detailed individual survey which includes information about their daily social contacts and we use the union of these contacts to form their social network links.
- We study three dummy variables related to villagers' working status – work or not, work outside of the village or not, and work in a private company or not.

Network Data Sets

China telecom networks:

- China telecommunication network data was obtained from a major Chinese mobile carrier (China Telecom), which gave us access to its entire customer base in two medium-sized cities in Sichuan province.
- For each customer, we know age, gender, location, phone model, and phone usage. Beside, the Call Detailed Record allows us to construct links between users (a link is placed between two individuals when they have called or texted each other within the same month).
- We first obtain a sample of 26,000 customers by a snowball sampling initiated from Samsung Note II adopters. Then we follow Blondel et al. (2008) and use the Louvain method to construct 155 non-overlapping network communities from the snowball sample.
- We study three dummy variables related to phone model adoption – Samsung noteII, highend, and brand.

Main findings

- Individual degree and eigenvector centralities and desirable behaviors are positively associated. The individual clustering coefficient has a negative effect on working and product adoption (consistent with the structural holes theory).
- Global network structures may show opposite effects through the direct correlated effect channel and through moderating the endogenous peer effect channel. In general we observe
  - higher average degree, variance of degree, and maximum and minimum eigenvalues strengthen peer influences.
  - longer average path and diameter hinder peer influences.
  - number of components has a negative but size of component has a positive effect on peer influence.
  - global clustering coefficient enhances the peer influence on product adoption (consistent with the network closure theory).
  - effects of assortativity and homophily on peer influences are subject to behavioral outcomes.

	GPA		smoking		club	
	Own	Contextual	Own	Contextual	Own	Contextual
male	-0.1750***	0.0224	-0.0430	-0.2812	-0.2990***	0.0400
	(0.0128)	(0.0221)	(0.1255)	(0.2252)	(0.0296)	(0.0531)
age	-0.0487***	-0.0085***	0.8733***	0.1121***	0.0008	-0.0092
	(0.0040)	(0.0027)	(0.0372)	(0.0279)	(0.0090)	(0.0066)
black	-0.1753***	-0.0364	-2.4673***	-1.5456***	0.3133***	-0.0257
	(0.0244)	(0.0314)	(0.2558)	(0.3331)	(0.0603)	(0.0785)
hisp	-0.1236***	-0.0661*	-0.4123*	-0.3777	0.1486***	0.0863
	(0.0236)	(0.0367)	(0.2449)	(0.3891)	(0.0577)	(0.0918)
asian	0.2478***	0.2091***	-0.4701	-1.2112**	0.2598***	0.1778
	(0.0326)	(0.0544)	(0.3293)	(0.5671)	(0.0776)	(0.1338)
other race	-0.1025***	-0.1870***	0.9111***	1.4117***	0.2133***	-0.2361**
	(0.0227)	(0.0441)	(0.2429)	(0.4503)	(0.0572)	(0.1062)
both parents	0.1283***	0.1873***	-1.0320***	-1.5136***	0.0704**	0.1181*
	(0.0139)	(0.0269)	(0.1436)	(0.2679)	(0.0338)	(0.0631)
less HS	-0.1256***	-0.1262***	0.7789***	0.8897**	-0.1193**	-0.3607***
	(0.0205)	(0.0370)	(0.2064)	(0.3972)	(0.0486)	(0.0936)
more HS	0.1800***	0.2723***	-0.2541*	-1.4179***	0.3506***	0.3749***
	(0.0146)	(0.0277)	(0.1485)	(0.2794)	(0.0350)	(0.0659)
Mom edu missing	-0.0220	-0.0106	-0.2122	-0.1084	-0.0816*	-0.1898**
	(0.0190)	(0.0355)	(0.1986)	(0.3704)	(0.0468)	(0.0873)
professional	0.1179***	0.0361	-0.0359	-0.0659	0.1464***	0.0895
	(0.0192)	(0.0376)	(0.2021)	(0.3896)	(0.0476)	(0.0919)
home	0.0598***	-0.0288	-0.3309	-0.3474	-0.0798*	0.1235
	(0.0196)	(0.0370)	(0.2034)	(0.3744)	(0.0480)	(0.0883)
other job	0.0393**	0.0039	0.0329	0.1508	0.0585	0.0992
	(0.0163)	(0.0340)	(0.1758)	(0.3444)	(0.0414)	(0.0812)
degc	2.5519***		-10.0553***		9.6621***	
	(0.4606)		(4.3455)		(1.1312)	
eigec	0.1777***		-1.6728***		1.0198***	
	(0.0441)		(0.4383)		(0.1080)	
cluster	0.0426		-0.7462***		0.0182	
	(0.0263)		(0.2717)		(0.0641)	
σ^2_ϵ	0.5174		55.2848		3.0672	
	(0.0055)		(0.5922)		(0.0328)	

	Work		Work outside Vill.		Work in Priv.	
	Own	Contextual	Own	Contextual	Own	Contextual
male	1.4386***	0.1159**	1.1118***	0.1171*	0.8283***	-0.0051
	(0.0361)	(0.0596)	(0.0387)	(0.0678)	(0.0333)	(0.0597)
age(10 yrs)	-0.0069***	0.0016	-0.0146***	-0.0051***	-0.0080***	-0.0032**
	(0.0009)	(0.0014)	(0.0011)	(0.0018)	(0.0009)	(0.0016)
native	-0.0460*	-0.1701***	-0.0394	-0.1075	-0.0920***	-0.2202***
	(0.0261)	(0.0563)	(0.0319)	(0.0690)	(0.0268)	(0.0582)
degc	4.8791***		-1.7578*		1.1673	
	(0.9405)		(0.9738)		(0.8471)	
eigec	-0.1462*		-0.0389		-0.2948***	
	(0.0846)		(0.0898)		(0.0794)	
cluster	-0.1325**		-0.0331		-0.0093	
	(0.0518)		(0.0612)		(0.0504)	

	NoteII adoption		Highend adoption		Brand adoption	
	Own	Contextual	Own	Contextual	Own	Contextual
male	0.0451	-0.0312	0.0111	0.0507	0.0496**	0.1043***
	(0.0369)	(0.0577)	(0.0222)	(0.0344)	(0.0215)	(0.0328)
age	0.0002	-0.0087***	0.0058***	0.0036**	0.0001	0.0023
	(0.0019)	(0.0025)	(0.0012)	(0.0015)	(0.0011)	(0.0015)
tenure	-0.0001	0.0128**	0.0139***	0.0076**	0.0127***	0.0122***
	(0.0036)	(0.0064)	(0.0022)	(0.0036)	(0.0022)	(0.0035)
Chengdu	-0.1524**	0.8598***	0.0018	0.2308***	0.1656***	0.4044***
	(0.0742)	(0.0988)	(0.0418)	(0.0699)	(0.0417)	(0.0691)
degc	7.7447***		2.5405***		2.4973***	
	(0.4184)		(0.2744)		(0.2845)	
eigec	-0.8918***		-0.3613***		-0.1348*	
	(0.1215)		(0.0793)		(0.0780)	
cluster	-0.2980***		-0.0651**		-0.0506*	
	(0.0553)		(0.0293)		(0.0281)	

AddHealth – GPA

	avedeg	vardeg	mineig	maxeig	avepath	numcomp	giantcomp	diam	assort	cluster	HI-sex	HI-race	HI-age	Factors
Peer Effect (random coef.)														
ζ_1	0.1566***	0.1812***	0.0820**	0.1406***	0.2960***	0.2421***	0.1724***	0.3086***	0.2455***	0.2665***	0.2835***	0.1697***	0.2782***	0.2376***
	(0.0202)	(0.0194)	(0.0411)	(0.0289)	(0.0372)	(0.0118)	(0.0181)	(0.0330)	(0.0211)	(0.0281)	(0.0997)	(0.0382)	(0.0423)	(0.0107)
ζ_2	0.0166***	0.0048***	0.0335***	0.0112***	-0.0146	-0.0002	0.0003***	-0.0080**	-0.0644	-0.1360	-0.0743	0.0907*	-0.0853	0.0248***
	(0.0038)	(0.0015)	(0.0087)	(0.0031)	(0.0084)	(0.0002)	(0.0001)	(0.0031)	(0.0851)	(0.1162)	(0.1531)	(0.0505)	(0.0780)	(0.0073)
														-0.0096
														(0.0070)
														0.0068
														(0.0085)
														-0.0217***
														(0.0071)
Global Network effect														
ρ	-0.0729***	-0.0239***	-0.1368***	-0.0532***	0.0707**	0.0024***	-0.0010***	0.0341***	0.2943	-0.1678	0.1438	-0.2965	0.5861***	-0.1223***
	(0.0127)	(0.0052)	(0.0300)	(0.0108)	(0.0319)	(0.0007)	(0.0002)	(0.0115)	(0.3000)	(0.3923)	(0.5777)	(0.1838)	(0.2856)	(0.0243)
														0.0320
														(0.0235)
														0.0159
														(0.0277)
														0.0746***
														(0.0253)
Own	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Contextual	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
σ^2_ϵ	0.4989	0.4993	0.4990	0.4991	0.4997	0.4998	0.4995	0.4997	0.4999	0.4998	0.4998	0.5000	0.4998	0.5001
	(0.0059)	(0.0059)	(0.0061)	(0.0060)	(0.0061)	(0.0062)	(0.0059)	(0.0061)	(0.0060)	(0.0061)	(0.0062)	(0.0061)	(0.0062)	(0.0062)
σ^2_ν	0.0263	0.0288	0.0278	0.0275	0.0338	0.0289	0.0300	0.0339	0.0350	0.0339	0.0350	0.0349	0.0337	0.0261
	(0.0061)	(0.0065)	(0.0063)	(0.0062)	(0.0073)	(0.0065)	(0.0068)	(0.0073)	(0.0078)	(0.0073)	(0.0076)	(0.0075)	(0.0071)	(0.0059)
σ^2_ξ	0.0014	0.0014	0.0014	0.0014	0.0014	0.0014	0.0014	0.0014	0.0014	0.0014	0.0014	0.0014	0.0014	0.0014
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)

Indian village – work or not

	avedeg	vardeg	mineig	maxeig	avepath	numcomp	giantcomp	diam	assort	cluster	HI-sex	HI-native	Factors
Peer Effect (random coef.)													
ζ_1	-0.3061***	0.1873***	-0.2230	-0.1452	0.7087***	0.4141***	0.2223***	0.5653***	0.3288***	0.2318	-0.3825	-0.5846	0.3214***
	(0.1256)	(0.0637)	(0.1778)	(0.1482)	(0.2505)	(0.0419)	(0.0807)	(0.1403)	(0.0329)	(0.1478)	(0.2476)	(0.3548)	(0.0257)
ζ_2	0.1022***	0.0111**	0.1056***	0.0518***	-0.1033	-0.0278**	0.0004	-0.0294*	-0.0787	0.4339	1.0239***	1.5062***	0.0571***
	(0.0196)	(0.0052)	(0.0337)	(0.0160)	(0.0675)	(0.0104)	(0.0003)	(0.0171)	(0.2940)	(0.6954)	(0.3538)	(0.5874)	(0.0193)
													-0.0151
													(0.0221)
													0.0684***
													(0.0218)
													0.0101
													(0.0204)
Global Network effect													
ρ	-0.0126	0.0074	0.0310	0.0147	0.1229**	0.0233**	0.0007**	0.0221	0.3150	-0.4207	0.4695	0.8250	0.0304
	(0.0243)	(0.0057)	(0.0383)	(0.0170)	(0.0663)	(0.0096)	(0.0003)	(0.0180)	(0.2972)	(0.7094)	(0.3525)	(0.5616)	(0.0227)
													0.0554**
													(0.0222)
													0.0225
													(0.0205)
													0.0044
													(0.0216)
Own	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Contextual	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
σ_ν^2	0.0201	0.0200	0.0190	0.0197	0.0205	0.0194	0.0201	0.0207	0.0218	0.0223	0.0207	0.0200	0.0175
	(0.0053)	(0.0049)	(0.0047)	(0.0049)	(0.0054)	(0.0052)	(0.0049)	(0.0050)	(0.0055)	(0.0057)	(0.0054)	(0.0050)	(0.0047)
σ_ξ^2	0.0120	0.0154	0.0134	0.0144	0.0174	0.0166	0.0181	0.0177	0.0188	0.0188	0.0148	0.0148	0.0120
	(0.0036)	(0.0049)	(0.0037)	(0.0042)	(0.0053)	(0.0045)	(0.0054)	(0.0054)	(0.0054)	(0.0052)	(0.0047)	(0.0047)	(0.0039)

China telecom – Highend phone adoption

	avedeg	vardeg	mineig	maxeig	avepath	diam	assort	cluster	HI-sex	HI-Chengdu	factor
Peer Effect (random coef.)											
ζ_1	-0.0199	0.0441**	-0.0095	-0.0466	0.2980***	0.2416***	0.1246***	-0.0883**	-0.2973**	0.1952	0.1028***
	(0.0260)	(0.0206)	(0.0599)	(0.0284)	(0.0658)	(0.0629)	(0.0222)	(0.0382)	(0.1455)	(0.2435)	(0.0187)
ζ_2	0.0171***	0.0006***	0.0152	0.0095***	-0.0537***	-0.0156**	0.3936***	0.6459***	0.5792**	-0.1218	0.0715***
	(0.0033)	(0.0002)	(0.0095)	(0.0018)	(0.0159)	(0.0060)	(0.1049)	(0.1357)	(0.2218)	(0.2606)	(0.0198)
											-0.0501***
											(0.0189)
											0.0629***
											(0.0181)
											0.0292*
											(0.0177)
Global Network effect											
ρ	-0.0028	-0.0001	-0.0187**	-0.0006	0.0446***	0.0169***	0.2131**	-0.0131	0.2606	-0.2712	-0.0090
	(0.0029)	(0.0001)	(0.0096)	(0.0017)	(0.0145)	(0.0054)	(0.0973)	(0.1328)	(0.2089)	(0.2411)	(0.0155)
											0.0421**
											(0.0165)
											-0.0104
											(0.0176)
											0.0595***
											(0.0167)
Own	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Contextual	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
σ_ν^2	0.0237	0.0240	0.0234	0.0243	0.0213	0.0215	0.0227	0.0230	0.0240	0.0242	0.0194
	(0.0049)	(0.0050)	(0.0047)	(0.0047)	(0.0044)	(0.0044)	(0.0046)	(0.0045)	(0.0049)	(0.0047)	(0.0041)
σ_ξ^2	0.0150	0.0160	0.0203	0.0143	0.0174	0.0199	0.0196	0.0177	0.0187	0.0215	0.0142
	(0.0045)	(0.0042)	(0.0056)	(0.0043)	(0.0045)	(0.0056)	(0.0055)	(0.0044)	(0.0051)	(0.0052)	(0.0043)

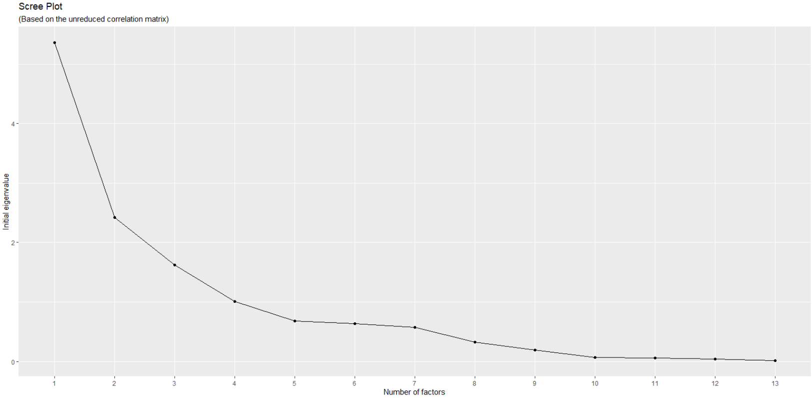
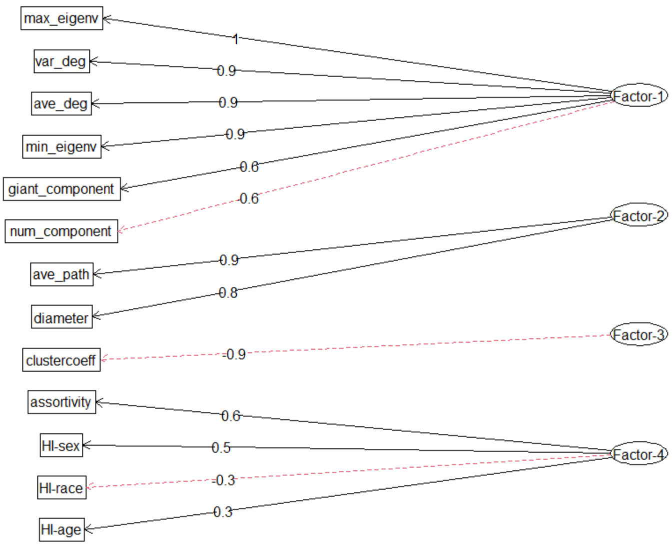


Figure: number of factors – Addhealth


max_eigenv
var_deg
ave_deg
min_eigenv
giant_component
num_component
ave_path
diameter
clustercoeff
assortivity
Hl-sex
Hl-race
Hl-age
Factor-1
Factor-2
Factor-3
Factor-4
1
0.9
0.9
0.9
0.6
-0.6
0.9
0.8
-0.9
0.6
0.5
-0.3
0.3

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