Co-worker networks and wage dynamics in firms

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Co-worker networks and labor mobility in economic geography

- Skill combination in firms is central to understand wage dynamics, urban wage premium and workplace polarization and firm growth.
- Labor mobility is frequently used to infer on combination of new knowledge with existing knowledge in the firm.

Boschma et al. (2009) RS; Csáfordi et al. (2020) JTT

• Skill combination happens through co-worker interaction.

Hansen (1999) ASQ; Reagans and McEvily (2003) ASQ

 Co-worker collaboration within and between the firm help performance. Connections of mobile workers matter for the firm.

Fleming – Mingo – Chen (2007) ASQ; Kemeny – Feldman – Ethridge – Zoller (2016) JEG; Tóth – Lengyel (2019) JTT



 We lack the understanding how co-worker networks boost skill combination and firm growth.

Co-worker networks across firms from admin data

Co-worker networks between firms are generated by labor mobility



Labor productivity in regions facilitated not only by A-B and A-C links but by B-C links as well.

Aggregation of individual level networks





Lengyel and Eriksson (2017) Journal of Economic Geography

Co-worker networks in geography

The effect of coworker networks on regional growth of income depends on region size

(ABSSPEC)



Eriksson and Lengyel (2019) Economic Geography

Policy relevance

Individual benefits through co-worker ties

Baranowska-Rataj, Elekes, Eriksson (2021) Boza and Ilyés (2020)

Clusters: the classic Silicon Valley vs Route 128 comparison

- California regulation allowed for hiring IT specialists away from competitors contrary to the MA regulation
- The network of former colleagues boost knowledge flows







Previous co-worker network: homophily assumption

$$P_{ij} = \frac{\ln N}{N} + \sum_{G=1}^{M} \left(\frac{\ln N_m}{N_m} / \frac{N_m}{N}\right) \times \delta_{ij}$$

where $G \in \{1, 2, ..., M\}$ denotes employee characteristics, N is the size of the workplace, N_m is the group size with characteristics m, and δ_{ij} equals 1, if i and j are similar according to m, otherwise 0.

Probability of ties are inversely proportional to the size of the workplace (Erdős and Rényi 1959).

Co-workers are more likely to know each other if they are similar (Currarini et al. 2009, Econometrica, Granovetter 1995, UCP; Kossinets and Watts 2006, Science; McPherson et al. 2001, ARS).

Similarity adds more to probability if there are few similar co-workers in a given characteristic.





Aim of the paper

To generate co-worker networks from administrative data that enables us to investigate inter-company connections.



In this presentation, we

- collect data from 10% of the employees in a local industry in Sweden;
- 2. map co-worker networks with a survey and using LinkedIn data;
- 3. estimate determinants of co-worker links such that parameters can refer to administrative data;
- 4. simulate random and dynamic co-worker networks in the administrative data using estimates from 3;
- 5. estimate wage dynamics of firms.



ICT industry growth in Umea



ICT sector employment growth in Umeå and Sweden, years 1990–2016.



Number of establishments in the ICT industry of Umeå, years 2000-2016.



Data

I. Survey

214 IT workers in 16 ICT firms in Umea (80% coverage in all firms)

- 1. Who do ask professional advice from?
- 2. Who do you co-operate with to do your job?
- 3. Who do you socialize with?

Demographic data: gender, age, education

II. LinkedIn

Respondents were asked to connect us on LinkedIn.

Career information



Lőrincz et al. Clusters, Global Innovation Networks

Co-worker link estimation

Determinants of co-worker relations within firms, logarithmic regression with firm random effects

	Coefficient	S.E.
Male-Male	0.580***	(0.102)
Female-Female	0.829***	(0.265)
Female-Male	-0.054	(0.165)
University-University	0.515***	(0.133)
High school-High school	0.489*	(0.282)
High school-University	0.327**	(0.165)
Same Generation	-0.166*	(0.100)
Years Co-worked	0.045*	(0.028)
Firm Size	-0.055	(0.045)
Constant	-0.416	(0.677)
N. of observations	3,056	
Log Likelihood	-1,786.386	
Akaike IC	3,594.773	
Bayesian IC	3,661.046	

Table 1. Estimations of co-worker links

Notes: *** p<0.001, ** p<0.01, * p<0.05



Simulation of co-worker networks from administrative data

- ASTRID Data:
 - Employee-employer matched dataset; Age, gender, education, work history
 - 1996-2016

$$L_{ij}(t) = \begin{cases} 1 & \text{if } U(0,1) < \hat{P}(i_{g,a,e}, j_{g,a,e}, ij_{co-work, firmsize}) \\ 0 & \text{otherwise} \end{cases}$$

- We establish links within companies.
- Ties are kept fixed even if one or both co-workers left the company.
- Labor mobility creates links across firms:

 $w_{ab,t} = \sum_{ij,t} L_{ij,t} \, ; \, i \epsilon a, j \epsilon b$



Variables from the firm network

- Constraint: describes redundancy/cohesion in the ego-network of companies $C_{a} = \sum_{b \in V_{a,a \neq b}} \left(\sum_{q \in V_{a,k \neq a,b}} p_{a,b} + p_{a,k} p_{k,b} \right)^{2} \qquad p_{a,b} = \frac{w_{a,b} + w_{b,a}}{\sum_{k \in V_{a,k \neq b}} (w_{a,k} + w_{k,a})}$
- Closeness centrality: describes access of companies in the full network



$$C_a^{cl} = \frac{n-1}{\sum_{a \neq b} \ell(a, b)}$$



The evolution of network variables



2015



Estimation framework

• Fixed-effect regression with lagged dependent variable: how does average wage increase as network position of the firm change? $y_{a,t+1} = \propto +y_{a,t} + \beta_1 Strength_{at} + \beta_2 C_{at}^{cl} + \beta_3 C_{at} + \beta_4 Strength_{at} x Size_{at} + \beta_5 C_{at}^{cl} x Size_{at} + \beta_5 C_{$

 $y_{a,t+1} = \alpha + y_{a,t} + \beta_1 Strengtn_{at} + \beta_2 C_{at}^{at} + \beta_3 C_{at} + \beta_4 Strengtn_{at} x Stze_{at} + \beta_5 C_{at}^{at} x Stze_{at} + \beta_5 C_{at}^{at}$

- **Controls:** incoming and outgoing human capital, firm size (log number of employees), the share of female employees
- Human capital measure to decrease endogeneity (Csáfordi et al. 2020)



$$wage_{m,a,t} = \propto +\beta z_{m,t} + \theta_m + \varphi_i + \varepsilon_{m,a,t}$$

 $HC_{m,t} = \hat{\beta} z_{m,t} + \hat{\theta}_m$

Estimations across network realizations

- We have generated 25 random networks
- Ran the regressions on variables calculated from these networks
- Calculated pooled coefficients and standard errors from the 25 models applying Rubin's rules (Rubin, 2004)

$$\underline{\beta} = \frac{1}{r} \left(\sum_{g=1}^{r} \theta_g \right) \qquad SE_{Pooled} = \sqrt{\frac{1}{r} \sum_{g=1}^{r} SE_g^2 + \left(1 + \frac{1}{r}\right) \frac{\sum_{g=1}^{r} (\theta - \underline{\theta})^2}{r-1}}$$



1: baseline	2: network	3: extended
mean income (log)	mean income (log)	mean income (log)
0.297***	0.297***	0.297***
(0.0025)	(0.0025)	(0.0026)
0.0004	0.0004	0.0004
(0.0010)	(0.0010)	(0.0010)
-0.0045***	-0.0045***	-0.0045***
(0.0013)	(0.0013)	(0.0013)
-0.0012	-0.0012	-0.0012
(0.0012)	(0.0012)	(0.0012)
0.0492***	0.0494***	0.0465***
(0.0045)	(0.0045)	(0.0045)
tion network)		
	0 0000	0 0000
	(0.0000)	(0.0000)
	9.392**	11.314*
	(3.391)	(5.7415)
	-0.0133**	-0.0258***
	(0.0041)	(0.0068)
		0.0001
		(0.0000)
		-3 2012
		(6 8029)
		0.0200*
		(0.0082)
176 596	176 506	176 506
30 480	30 480	30 480
	1: baseline mean income (log) 0.297*** (0.0025) 0.0004 (0.0010) -0.0045*** (0.0013) -0.0012 (0.0012) 0.0492*** (0.0045) ion network)	1: baseline mean income (log) 2: network mean income (log) 0.297*** 0.297*** (0.0025) (0.0025) 0.0004 0.0004 (0.0010) (0.0010) -0.0045*** -0.0045*** (0.0013) (0.0013) -0.0012 -0.0012 (0.0012) (0.0012) 0.0492*** 0.0494*** (0.0045) (0.0045) ion network) 0.0000 9.392** (3.391) -0.0133** (0.0041) 176,586 176,586 39,489 39,489

Notes: Pooled coefficients (and standard errors in parentheses) of 25 regressions with firm fixed-effects. Additional controls: year dummies. *** p<0.001, ** p<0.01, * p<0.05

Estimation results

Figure 2. Coefficients and confidence intervals of the constraint (A) and closeness centrality (B) from the 25 simulations













Summary

- In this paper we establish a framework to create realistic co-worker networks from administrative data using small surveys and estimating relationships.
- Findings suggest that central positions of the firm in the co-worker network favor wage dynamics. Firms and employees can benefit from access in the full network of the labor market.
- Diverse access in the direct neighborhoods are more beneficial. However, cohesive networks can support large firms because they have to process larger pool of knowledge.



Thank you for your attention!

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https://www.mtakti.hu/wp-content/uploads/2021/may/CERSIEWP202118.pdf



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