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.
  

- 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.

Co-worker networks in geography

The effect of co-worker 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

\[ P_{ij} = \frac{\ln N}{N} + \sum_{g=1}^{M} \left( \frac{\ln N_{m}}{N_{m}} / \frac{N_{m}}{N} \right) \delta_{ij} \]

where \( G \in \{1, 2, \ldots, M\} \) denotes employee characteristics, \( N \) is the size of the workplace, \( N_m \) is the group size with characteristics \( m \), and \( \delta_{ij} \) 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

1. 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.

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

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male-Male</td>
<td>0.580***</td>
<td>(0.102)</td>
</tr>
<tr>
<td>Female-Female</td>
<td>0.829***</td>
<td>(0.265)</td>
</tr>
<tr>
<td>Female-Male</td>
<td>-0.054</td>
<td>(0.165)</td>
</tr>
<tr>
<td>University-University</td>
<td>0.515***</td>
<td>(0.133)</td>
</tr>
<tr>
<td>High school-High school</td>
<td>0.489*</td>
<td>(0.282)</td>
</tr>
<tr>
<td>High school-University</td>
<td>0.327**</td>
<td>(0.165)</td>
</tr>
<tr>
<td>Same Generation</td>
<td>-0.166*</td>
<td>(0.100)</td>
</tr>
<tr>
<td>Years Co-worked</td>
<td>0.045*</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Firm Size</td>
<td>-0.055</td>
<td>(0.045)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.416</td>
<td>(0.677)</td>
</tr>
</tbody>
</table>

N. of observations: 3,056
Log Likelihood: -1,786.386
Akaike IC: 3,594.773
Bayesian IC: 3,661.046

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

\[ L_{ij}(t) = \begin{cases} 1 & \text{if } U(0, 1) < \hat{P}(i,g,a,e,j,g,a,e,i,j\text{co-work},\text{firmsize}) \\ 0 & \text{otherwise} \end{cases} \]

• 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:

\[ w_{ab,t} = \sum_{i,j,t} L_{ij,t} ; i_{ea}, j_{eb} \]
Variables from the firm network

- Constraint: describes redundancy/cohesion in the ego-network of companies

\[ C_a = \sum_{b \in \mathcal{V}_a, a \neq b} \left( \sum_{q \in \mathcal{V}_{a,k \neq a,b}} p_{a,b} + p_{a,k} p_{k,b} \right)^2 \quad p_{a,b} = \frac{w_{a,b} + w_{b,a}}{\sum_{k \in \mathcal{V}_{a,k \neq b}} (w_{a,k} + w_{k,a})} \]

- 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

A: Average degree and strength

B: Constraint and closeness centrality
Estimation framework

• Fixed-effect regression with lagged dependent variable: how does average wage increase as network position of the firm change?

\[ y_{a,t+1} = \alpha + y_{a,t} + \beta_1 \text{Strength}_{at} + \beta_2 \text{Cat}_{at} + \beta_3 \text{Cat}_{at} + \beta_4 \text{Strength}_{at} \times \text{Size}_{at} + \beta_5 \text{Cat}_{at} \times \text{Size}_{at} + \beta_6 \text{Cat}_{at} \times \text{Size}_{at} + w_{a,t} + \text{controls}_{a,t} + \xi_a + \varepsilon_{at} \]

• 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)

\[ \text{wage}_{m,a,t} = \alpha + \beta \text{z}_{m,t} + \theta_m + \phi_i + \varepsilon_{m,a,t} \]

\[ \text{HC}_{m,t} = \beta \text{z}_{m,t} + \theta_m \]
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)

\[ \beta = \frac{1}{r} \left( \sum_{g=1}^{r} \theta_g \right) \]

\[ SE_{Pooled} = \sqrt{ \frac{1}{r} \sum_{g=1}^{r} SE_g^2 + \left( \frac{1}{r} \right) \left( \frac{\sum_{g=1}^{r} (\theta - \bar{\theta})^2}{r-1} \right) \} } \]
### Estimation results

<table>
<thead>
<tr>
<th>Firm characteristics (t-1)</th>
<th>1: baseline mean income (log)</th>
<th>2: network mean income (log)</th>
<th>3: extended mean income (log)</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean income (log)</td>
<td>0.297*** (0.0025)</td>
<td>0.297*** (0.0025)</td>
<td>0.297*** (0.0026)</td>
</tr>
<tr>
<td>HC in (log)</td>
<td>0.0004 (0.0010)</td>
<td>0.0004 (0.0010)</td>
<td>0.0004 (0.0010)</td>
</tr>
<tr>
<td>HC out (log)</td>
<td>-0.0045*** (0.0013)</td>
<td>-0.0045*** (0.0013)</td>
<td>-0.0045*** (0.0013)</td>
</tr>
<tr>
<td>Share women (log)</td>
<td>-0.0012 (0.0012)</td>
<td>-0.0012 (0.0012)</td>
<td>-0.0012 (0.0012)</td>
</tr>
<tr>
<td>Size (log N employees)</td>
<td>0.0497*** (0.0045)</td>
<td>0.0494*** (0.0045)</td>
<td>0.0465*** (0.0045)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Network position (t-1) (information network)</th>
<th>1: baseline mean income (log)</th>
<th>2: network mean income (log)</th>
<th>3: extended mean income (log)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strength</td>
<td>0.0000 (0.0000)</td>
<td>0.0000 (0.0000)</td>
<td></td>
</tr>
<tr>
<td>Closeness centrality</td>
<td>9.392** (3.391)</td>
<td>11.314* (5.7415)</td>
<td></td>
</tr>
<tr>
<td>Constraint</td>
<td>-0.0133** (0.0041)</td>
<td>-0.0258*** (0.0068)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Interactions (t-1)</th>
<th>1: baseline mean income (log)</th>
<th>2: network mean income (log)</th>
<th>3: extended mean income (log)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strength x Size</td>
<td>0.0001 (0.0000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Closeness centr x Size</td>
<td>-3.2012  (6.80129)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constraint x Size</td>
<td>0.0200* (0.0082)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| N (firm x year)    | 176.586  | 176.586  | 176.586  |
| N (firms)          | 39.489   | 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

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