The Effects of Social Networks on Employment and Inequality

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(Presented by Joanna Drummond)
Problem

• Hypothesis: Social networks are a manner of obtaining information about job opportunities

• Goal: Develop a model that captures this dynamic; use model to:
  – Explore basic characteristics and dynamics of the model
  – Explore dynamics of drop-outs
Motivation

• Strong relationship between social networks and labor markets
  – Granovetter (1973, 1995) survey, 50% of jobs obtained through social contacts
  – Rees (1966) > 60%

• Participation (drop-outs) in labor force is different for different groups
  – (e.g., (Card and Krueger 1992), (Chandra 2000), (Heckman et al. 2000))
Motivation

• Positive correlations of employment & social networks present in the data
  – Topa (2001) geographic correlation in unemployment across neighborhoods, also positive amount of social interactions
Outline

• Problem
• Motivation
• Description of Model
  – Intuitive Description
  – Formal Description
• Dynamics & Patterns of Employment
• Dynamics & Patterns of Dropouts
• Discussion (including Policy Implications)
Intuitive Description of Model

• Agents get job information both randomly, and through already-employed friends
  – Unemployed agents connected to employed friends have a better chance of hearing about jobs
  – Friends pass on jobs only if they don’t want the job themselves
  – Positive correlation between connected agents’ employment status
    • Dropping out has a contagion effect
Simplifying Assumptions

• Social network is given & fixed
  – And undirected
• All jobs are identical
  – (Cavaló-Armegol & Jackson 2002 relax this assumption)
• Discretized time
• Agents hear about a job exogenously with probability $a$ and lose jobs exogenously with probability $b$ during any given time period
• Once an agent drops out of the job market, they do not reenter
• Agents never leave the social network
Notation & Setup

• \( n \) agents, time periods indexed by \( t \)
• Social network given by \( g \)
  – \( g_{ij} = 1 \) iff agents \( i \) & \( j \) know each other;
  – \( g_{ij} = 1 \leftrightarrow g_{ji} = 1 \)
• Employment vector \( s \)
  – \( s_{it} = 1 \) iff agent \( i \) employed at time \( t \)
• Agents \( i \) and \( j \) are *path-connected* if under \( g \) there exists a sequence of links that form a path from \( i \) to \( j \)
Formal Description of Model
(Without Drop outs)

- Each participant hears of a job with probability $a$; lose job with probability $b$
- Probability agent $i$ learns about a job & $j$ takes it $p_{ij}(s)$:

\[
p_{ij}(s) = \begin{cases} 
  a & \text{if } s_i = 0 \text{ and } i = j, \\
  \frac{a}{\sum_{k:s_k=0} g_{ik}} & \text{if } s_i = 1, s_j = 0, \text{ and } g_{ij} = 1; \text{ and} \\
  0 & \text{otherwise,}
\end{cases}
\]
Dynamics of Model

• Tension between short-term & long-term dynamics
  – Friends are competitors for job information in the short run
  – Friends help keep their friends employed

• Employment can be modeled as a finite state Markov process
  – State: \( s \)
  – Transitions: dependent on network properties
Dynamics of Model

• Evaluate relationships
  – For systems with multiple agents, empirically evaluated using hundreds of thousands of time periods
  • Unless otherwise noted, empirical evaluation done with $a = 0.100$ and $b = 0.015$
    – If $t = 1$ week, equivalent to directly hearing about a job every 10 weeks, and losing a job every 67 weeks
Dynamics of Model

- Average unemployment & agents’ employment correlation dependent on network structure

<table>
<thead>
<tr>
<th>$g$</th>
<th>$\text{Prob}(s_1 = 0)$</th>
<th>$\text{Corr}(s_1, s_2)$</th>
<th>$\text{Corr}(s_1, s_3)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.132</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>1 4</td>
<td>0.083</td>
<td>0.041</td>
<td>—</td>
</tr>
<tr>
<td>2 3</td>
<td>0.063</td>
<td>0.025</td>
<td>0.019</td>
</tr>
<tr>
<td>1 4</td>
<td>0.050</td>
<td>0.025</td>
<td>0.025</td>
</tr>
</tbody>
</table>
Dynamics of Model

- Structure matters; Path length matters

<table>
<thead>
<tr>
<th>$g$</th>
<th>$\text{Prob}(s_1 = 0)$</th>
<th>$\text{Corr}(s_1, s_2)$</th>
<th>$\text{Corr}(s_1, s_3)$</th>
<th>$\text{Corr}(s_1, s_4)$</th>
<th>$\text{Corr}(s_1, s_5)$</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Graph 1" /></td>
<td>0.060</td>
<td>0.023</td>
<td>0.003</td>
<td>0.001</td>
<td>-</td>
</tr>
<tr>
<td><img src="image2.png" alt="Graph 2" /></td>
<td>0.030</td>
<td>0.014</td>
<td>0.014</td>
<td>0.014</td>
<td>0.014</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$g$</th>
<th>Average Path Length</th>
<th>Average Unemployment</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image3.png" alt="Graph 3" /></td>
<td>1.571</td>
<td>0.048</td>
</tr>
<tr>
<td><img src="image4.png" alt="Graph 4" /></td>
<td>1.786</td>
<td>0.049</td>
</tr>
</tbody>
</table>
Dynamics of Model

- Structure Matters
Theoretical Results for Model

Proposition 1:

Under fine enough subdivisions of periods, the unique steady-state long run distribution on employment is such that the employment statuses of any path-connected agents are positively correlated.

“Proof:”

Uses properties of the Markov chain, namely properties of the transition matrix.
Theoretical Results for Model

Proposition 2:

Under fine enough subdivisions of periods, starting under the steady-state distribution, employment statuses of any two path-connected agents are positively correlated across arbitrary periods.

“Proof:”

Follows from Proposition 1, and induction on dominating transition matrices, making the transition matrices big enough.
Properties of the Model

• “Stickiness”:
  – Either extreme tends to stay at the extreme
  – Length of unemployment --> likelihood that agents’ connections are unemployed
  – Tends to oscillate between mostly employed or mostly unemployed
    • “Boom” & “Bust” effects
    • May be asynchronous across different parts of network
Properties of the Model

Proposition 3:

Under fine enough subdivisions of periods and starting under the steady-state distribution, the conditional probability that an individual will become employed in a given period is decreasing with the length of their observed (individual) unemployment spell.
Model with Dropouts

• Same as before, except:
  – Agents can drop out, without re-entry
  – All agents make decision simultaneously
  – Cost of staying in the network $c_i$, drawn uniformly from $[0.8, 1]$; wage $w = 1$
    • Agents have net payoff of: $0.1s_i + 0.9p_i - c_i$
      (where $s_i$ is $i$’s starting employment state; $p_i$ is $i$’s steady state employment probability in the maximal equilibrium of the drop-out game; discount of 0.9)
  – When agents drop out, they say “no” to all jobs
Model Properties

• Decision to stay in the labor force is strategic
  – Drop-out game is supermodular
    • Guarantees existence of maximal Nash equilibrium in pure strategies
    • Supermodularity gives emergence of contagion effects
Empirical Explorations of Model, Contagion Effects

- Fully connected

### Table 2—Dropouts and Contagion—Starting Employed

<table>
<thead>
<tr>
<th>s₀ = (1, ..., 1)</th>
<th>n = 1</th>
<th>n = 2</th>
<th>n = 4</th>
<th>n = 8</th>
<th>n = 16</th>
<th>n = 32</th>
<th>n → ∞</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drop-out percentage</td>
<td>58.3</td>
<td>44.5</td>
<td>26.2</td>
<td>14.7</td>
<td>9.7</td>
<td>7.8</td>
<td>6.8</td>
</tr>
<tr>
<td>Percentage due to contagion</td>
<td>0</td>
<td>8.8</td>
<td>5.0</td>
<td>1.4</td>
<td>0.4</td>
<td>0.2</td>
<td>0</td>
</tr>
</tbody>
</table>

### Table 3—Dropouts and Contagion—Starting Unemployed

<table>
<thead>
<tr>
<th>s₀ = (0, ..., 0)</th>
<th>n = 1</th>
<th>n = 2</th>
<th>n = 4</th>
<th>n = 8</th>
<th>n = 16</th>
<th>n = 32</th>
<th>n → ∞</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drop-out percentage</td>
<td>100</td>
<td>97.8</td>
<td>92.9</td>
<td>82.2</td>
<td>68.0</td>
<td>60.6</td>
<td>56.8</td>
</tr>
<tr>
<td>Percentage due to contagion</td>
<td>0</td>
<td>12.1</td>
<td>21.7</td>
<td>18.9</td>
<td>8.7</td>
<td>3.0</td>
<td>0</td>
</tr>
</tbody>
</table>
Properties of the Model

Proposition 4:

Consider two social groups with identical network structures. If the starting state person-by-person is higher for one group than the other, then the set of agents who drop out of the first group in the maximal equilibrium is a subset of their counterparts in the second group. These differences in drop-out rates generate persistent inequality in probabilities of employment in the steady-state distributions, with the first group having weakly better employment probabilities than their counterparts. There is a strict difference in employment probabilities for all agents in any component of the network for which the equilibrium drop-out decisions differ across the two groups.
More Empirical Explorations of the Model

![Graph Image]

**Table 4—Drop-Outs Rates in the Bridge Network with Asymmetric Starting States**

<table>
<thead>
<tr>
<th>Agent</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rate</td>
<td>0.47</td>
<td>0.42</td>
<td>0.42</td>
<td>0.42</td>
<td>0.42</td>
<td>0.91</td>
<td>0.93</td>
<td>0.93</td>
<td>0.93</td>
<td>0.93</td>
</tr>
</tbody>
</table>
Suggested Policy Implications

• Policies that affect current employment have delayed and long-lasting effects
• Positive externality between connected individuals
• Drop-out game: subsidizing certain agents may limit contagion effect
• Network effects are important for designing subsidy & affirmative action programs
Discussion/Future Work

• Loosen assumption of treating network as a given
  – Growing literature on formation of networks
• Look deeper at how information exchanges across networks
• Allow for the network to dynamically change
Added Discussion
(My thoughts)

• Models drop-out rates and unemployment rates consistently with previous empirical results

• How well does their model fit to actual data? Are there other models that fit better?
  – Do their policy suggestions hold?
Thank you!

Questions?