Paper Replication

The Effects of Social Networks on Employment and Inequality

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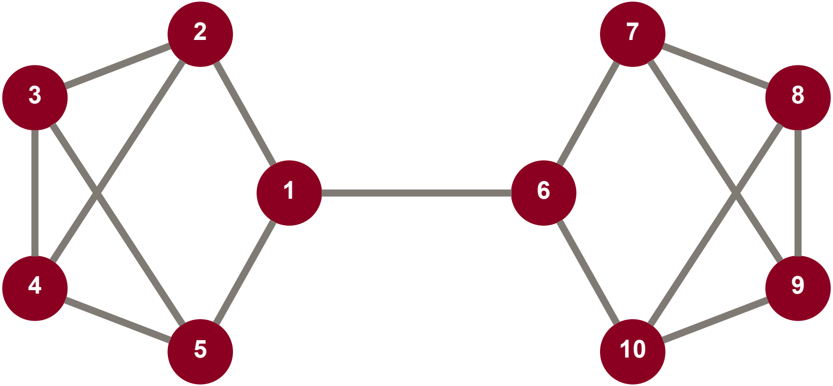
We develop a model where agents obtain information about job opportunities through an explicitly modeled network of social contacts. We show that employment is positively correlated across time and agents. Moreover, unemployment exhibits duration dependence: the probability of obtaining a job decreases in the length of time that an agent has been unemployed. Finally, we examine inequality between two groups. If staying in the labor market is costly and one group starts with a worse employment status, then that group's drop-out rate will be higher and their employment prospects will be persistently below that of the other group. (*JEL* A14, J64, J31, J70)

Simple networks for job transmission

Throughout vasts swaths of society, people hear about jobs and find employment through social contacts.

- The characteristics of the social networks that each person maintains affect their ability to stay employed and advance their careers.
- Simulations on a simple graph yield insights on these effects.
    - Nodes (vertices) are agents and edges are social connections.
    - Workers in the same graph component will have correlated employment histories.
    - More-closely connected nodes will be more correlated.
    - More-densely connected networks will have higher average employment.
    - Expected gains from employment in a given network structure affect probability of remaining in the labor force.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The Model

In each period:

- With probability $a = 0.1$, each agent receives a job offer.
- If the agent is unemployed, he keeps the offer; if he is unemployed, he transmits it to a random, currently unemployed “neighbor.”
  - Employment status is based on the “last period.”
  - Jobs can only be transmitted once.
- With probability $b = 0.015$, every job or accepted offer is destroyed.

A §II, Ex. 1a: given $\boldsymbol{s}_{t-1}$, s_{1t} and s_{3t} are negatively correlated.

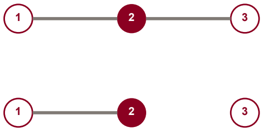
B §II, Ex. 1b: in the long run, agent 3 benefits agent 1.

C §II, Ex. 2: for the graphs shown, the probabilities and correlations below.

	$P(s_1 = 0)$	$\mathrm{Corr}(s_1, s_2)$	$\mathrm{Corr}(s_1, s_3)$
α	0.132	-	-
β	0.083	0.041	-
γ	0.063	0.025	0.019
δ	0.050	0.025	0.025

Expected unemployment and correlations, for $\alpha - \delta$. N.B. that these numbers are extremely imprecise – see footnotes 8 and 9.

Figure 1, $\boldsymbol{s}_{t-1}$



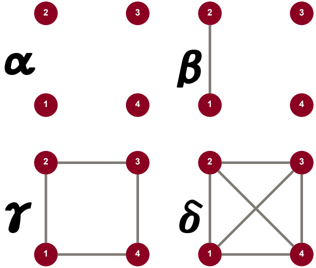


Figure 2

D §II, Ex. 2, ¶6: the networks shown demonstrate that the probability of unemployment falls in the number of links, and correlations between nodes fall with the length of the shortest path between them.

- For A, $\text{Corr}(s_1, s_2) > \text{Corr}(s_1, s_3) > \text{Corr}(s_1, s_4) > \text{Corr}(s_1, s_5)$.
- The average unemployment is 6% for A, and 3% for B.

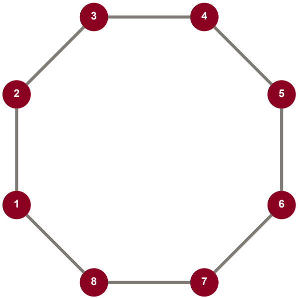


Figure 3A

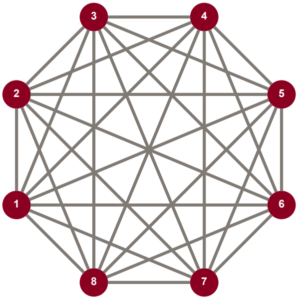


Figure 3B

What to confirm? [3 of 4]

- Ex. 3: even with equal numbers of links, the position in a network affects employment.
  - The average rates are: $\bar{s}_1 = 0.047$, $\bar{s}_2 = 0.048$, and $\bar{s}_3 = 0.05$.

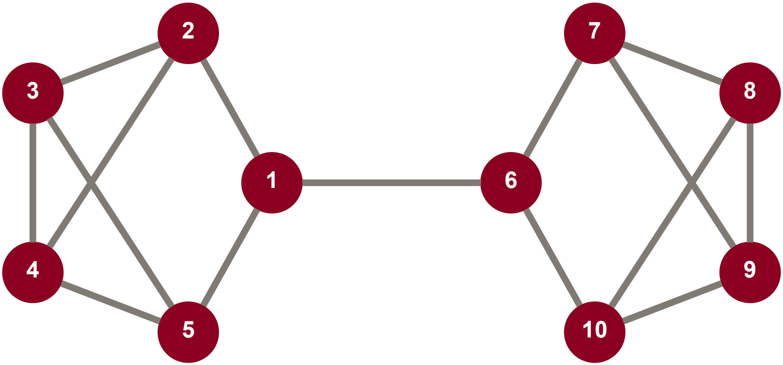


Figure 4

F Ex. 4: the average distance between nodes affects the long-run average employment, in the entire network.

- Average path lengths for A and B are 1.571 and 1.786.
- Average unemployment rates for A and B are 0.048 and 0.049.

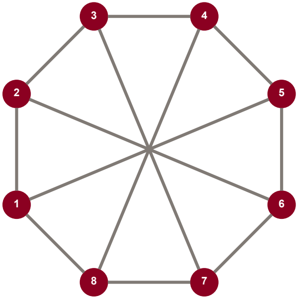


Figure 5A

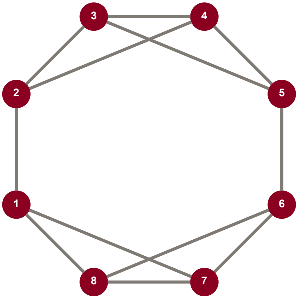


Figure 5B

Necessary Functionality

- Read in arbitrary graphs (trivial) and put them in a dictionary.
  - We'll use the **glob.glob()** function to list files.
  - I've provided json descriptions of all the graphs we'll consider.
- **Implement job creation, transmission, and loss mechanisms**
  - Save each agent's employment record for study
  - See **random.random()** – we'll want `random()` $< a$.
  - Use **random.choice()** to choose a random neighbor, or **random.shuffle()** to choose a random ordering of neighbors.
- Calculate employment rates
- Calculate correlations among agents
- Calculate minimum distance between agents

- Bonus make all this scriptable!

Implementing the Model! See `caj-ex/caj_tools.py`.

A Computational Shortcut

- Normally, the variance is $\sigma^2 = E[X^2] - E[X]^2$.
- But we have only two states (0 and 1), and $x = x^2$ for both of them.
- In that case, defining $\mu \equiv \overline{X}$,
$$\sigma^2 = \mu - \mu^2.$$

- As a reminder, the correlation is
$$\rho_{XY} = E[(X - \mu_X)(Y - \mu_X)]/(\sigma_X \sigma_Y).$$

Straightforward Extensions

In §IV, Calvó-Armengol and Jackson model drop-out rates with contagion, and different initial conditions (and costs to employment).

- Part-analytic calculation of exp. costs to staying in the labor force.

Two classes of people A and B, with different initial employment histories.

- Study time to convergence, for various levels of segregation.
- Allow the job obtention rate to depend on past employment history (over a certain number of periods).

Far more broadly: any number of agent-based models.