Network constraints on cities, careers, and economic resilience

Morgan R. Frank
How do workers’ skills shape their mobility?

- How do skill requirements shape careers?
- Is labelling an occupation as “cognitive” or “physical” enough?
- How do workers move through urban labor markets?
- What about between urban labor markets?
- Do skills determine the economic resilience of cities?
The Triumph of the City
Edward Glaeser

“Cities don't make people poor; they attract poor people. The flow of less advantaged people into cities from Rio to Rotterdam demonstrates urban strength, not weakness.”

“Some places will, however, be left behind. Not every city will succeed, because not every city has been adept at adapting to the age of information, in which ideas are the ultimate creator of wealth.”
Our reliance on high-skill vs low-skill

Work of the Past, Work of the Future. David Autor (MIT)

impact(c) = \sum_{j \in J} p_{auto}(j) \cdot \text{empShare}(j, c)

Pearson ρ = -0.53 (p_{val} < 10^{-28})

Frank et al,
Small cities face greater impact from automation,
High-skill & low-skill workers

Programmers & Machine Learning

Truck Drivers & Autonomous Vehicles
High-skill & low-skill workers

Surgeons & Robotics

Engineers & Drones

Bank Tellers & ATMs
Skills, labor, and cities

- differential impact of automation
- skill & wealth disparity
- spatial career mobility

Local Labor Markets

Occupations & Employment
- career trajectories
- viable retraining
- job polarization

Tasks & Skills
- interaction with technology
- skill complementarity
- education

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Unpacking the polarization of workplace skills

- differential impact of automation
- skill & wealth disparity
- spatial career mobility

- career trajectories
- viable retraining
- job polarization

- interaction with technology
- skill complementarity
- education
Network constraints on cities, careers, and economic resilience

Morgan R. Frank

School of Computing and Information

Low Wage
Middle Wage
High Wage

Change in Employment Share (%)

Relative Change
(100 \cdot \frac{X}{X_{1981}})

Year

Annual Wage Percentile

B
C

Local Labor Markets

Occupations & Employment

Tasks & Skills

Executive

Persuasion

Programmer

Stamina

Bartender

Vision

Mathematics

Computer Vision

* differential impact of automation
* skill & wealth disparity
* spatial career mobility

* career trajectories
* viable retraining
* job polarization

* interaction with technology
* skill complementarity
* education

Comparing occupations from skills

Air Traffic Controller

Surgeon

Network constraints on cities, careers, and economic resilience

Morgan R. Frank
Comparing occupations from skills

Network constraints on cities, careers, and economic resilience

Air Traffic Controller
- Glare Sensitivity
- Spatial Orientation
- Sound Localization
- Peripheral Vision

Surgeon
- Getting Information
- Retrieving Relevant Knowledge
- Active Listening
- Static Strength
- Stamina
- Gross Body Coordination
- Dynamic Strength

$$\text{skillsim}_{j,j'} = \frac{\sum_s \min(onet(j, s), onet(j', s))}{\sum_s \max(onet(j, s), onet(j', s))}$$
## Skill similarity predicts career mobility

Dependent Variable: $\log_{10}$ Job Transitions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skill Similarity ($\text{skillsim}_{j,j'}$)</td>
<td>0.392***</td>
<td>0.403***</td>
<td>0.416***</td>
<td>0.424***</td>
</tr>
<tr>
<td>Total Employment ($\log_{10} N_{j,j'}$)</td>
<td>0.271***</td>
<td>0.324***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cognitive/Physical Similarity ($CP_{j,j'}$)</td>
<td></td>
<td>0.172***</td>
<td>−0.005</td>
<td></td>
</tr>
<tr>
<td>$\text{skillsim}<em>{j,j'} \times CP</em>{j,j'}$</td>
<td>0.069***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{skillsim}<em>{j,j'} \times \log</em>{10} N_{j,j'}$</td>
<td>0.062***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$CP_{j,j'} \times \log_{10} N_{j,j'}$</td>
<td></td>
<td></td>
<td>0.040**</td>
<td></td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.155</td>
<td>0.183</td>
<td>0.219</td>
<td>0.237</td>
</tr>
<tr>
<td>adj. $R^2$</td>
<td>0.154</td>
<td>0.182</td>
<td>0.219</td>
<td>0.237</td>
</tr>
</tbody>
</table>

Mapping occupations with skill similarity

Occupation Type:
- Physical
- Cognitive

Network constraints on cities, careers, and economic resilience

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School of Computing and Information
Tracking career trajectories with skill similarity

Employment-Weighted Embeddedness: \[ w^{(c)}_i = \sum_{j \in \text{Jobs}} \text{skillsim}_{i,j} \cdot \text{share}(c, j) \]

Complementarity or Competition?
Workers decrease embeddedness over careers

Network constraints on cities, careers, and economic resilience
Decreasing embeddedness corresponds to higher wages

$\Delta \log_{10} w = \log_{10} \left( w_{i_2}^{(c_2)} \right) - \log_{10} \left( w_{i_1}^{(c_1)} \right)$
Decreasing embeddedness corresponds to higher wages

### Embeddedness Change:

\[
\Delta \log_{10} w = \log_{10} \left( w_{t_2}^{(c_2)} \right) - \log_{10} \left( w_{t_1}^{(c_1)} \right)
\]

<table>
<thead>
<tr>
<th>Variable</th>
<th>Burning Glass Resumes</th>
<th>FutureFit AI Resumes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
</tr>
<tr>
<td>Occupation Change Dummy (J)</td>
<td>(-0.021^{\text{**}})</td>
<td>(-0.024^{\text{**}})</td>
</tr>
<tr>
<td>Relocation Dummy (relocation)</td>
<td>(0.002^{\text{**}})</td>
<td>(-0.000)</td>
</tr>
<tr>
<td>Bachelors Degree Change (ΔB)</td>
<td>(0.683^{\text{**}})</td>
<td>(0.688^{\text{**}})</td>
</tr>
<tr>
<td>ΔB × relocation</td>
<td>(-0.000)</td>
<td>(0.002^{\text{**}})</td>
</tr>
<tr>
<td>ΔB × J</td>
<td>(0.043^{\text{**}})</td>
<td>(0.020^{\text{**}})</td>
</tr>
<tr>
<td>City Network PageRank Change (Δlog_{10} P)</td>
<td>(0.428^{\text{**}})</td>
<td>(2.205^{\text{**}})</td>
</tr>
<tr>
<td>Δlog_{10} P × relocation</td>
<td>(-0.063^{\text{**}})</td>
<td>(-0.582^{\text{**}})</td>
</tr>
<tr>
<td>Δlog_{10} J</td>
<td>(-0.001)</td>
<td>(0.005^{\text{**}})</td>
</tr>
<tr>
<td>Δlog_{10} P × ΔB</td>
<td>(0.001^{\text{*}})</td>
<td>(-0.002^{\text{**}})</td>
</tr>
</tbody>
</table>

### Empty Cell Change (Δlog_{10} ε)

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δlog_{10} ε × relocation</td>
<td>(-0.452^{\text{**}})</td>
<td></td>
<td></td>
<td></td>
<td>(-0.348^{\text{**}})</td>
<td></td>
</tr>
<tr>
<td>Δlog_{10} ε × J</td>
<td></td>
<td>(0.104^{\text{**}})</td>
<td></td>
<td></td>
<td>(0.068^{\text{**}})</td>
<td></td>
</tr>
<tr>
<td>Δlog_{10} ε × ΔB</td>
<td></td>
<td>(-0.074^{\text{**}})</td>
<td></td>
<td></td>
<td>(-0.088^{\text{**}})</td>
<td></td>
</tr>
<tr>
<td>Δlog_{10} ε × Δlog_{10} P</td>
<td></td>
<td>(0.015^{\text{**}})</td>
<td></td>
<td></td>
<td>(0.022^{\text{**}})</td>
<td></td>
</tr>
<tr>
<td>Δlog_{10} ε × Δlog_{10} P</td>
<td></td>
<td>(-0.000)</td>
<td></td>
<td></td>
<td>(0.002^{\text{**}})</td>
<td></td>
</tr>
</tbody>
</table>

### Dataset Details

- **Year F.E.:** Yes
- **Source City F.E.:** Yes
- **Destination City F.E.:** Yes

### Model Fit

- \(R^2 = 0.488\)
- adj. \(R^2 = 0.487\)

**Note:** Variables were centered and standardized.
The average combined embeddedness of city pairs predicts spatial mobility

\[
\hat{w}_{c,c'} = \sum_{j \in \text{Jobs}^{(c)} \cap \text{Jobs}^{(c')}} 1/(w_j^{(c)}w_j^{(c')})
\]

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>(\log_{10}) Total Migration</th>
<th>(\log_{10}) Total Enplaned Passengers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
</tr>
<tr>
<td>Total Employment</td>
<td>0.517**</td>
<td>0.339**</td>
</tr>
<tr>
<td>(\log_{10}(T_{c,c'}))</td>
<td>-0.385**</td>
<td>-0.394**</td>
</tr>
<tr>
<td>Distance (\log_{10}D_{c,c'})</td>
<td>0.348***</td>
<td>0.223***</td>
</tr>
<tr>
<td>Embeddedness (\hat{w}_{c,c'})</td>
<td>-0.022***</td>
<td></td>
</tr>
<tr>
<td>(\hat{w}<em>{c,c'} \times \log</em>{10}T_{c,c'})</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>(\hat{w}<em>{c,c'} \times \log</em>{10}D_{c,c'})</td>
<td>0.358</td>
<td>0.425</td>
</tr>
<tr>
<td>(R^2)</td>
<td>adj. (R^2)</td>
<td>p_{val} &lt; 0.1*, p_{val} &lt; 0.01**, p_{val} &lt; 0.001***</td>
</tr>
</tbody>
</table>

Variables were centered and standardized.

Average combined embeddedness moderates city size in spatial mobility
Network constraints on cities, careers, and economic resilience

Morgan R. Frank

MEASURING SKILL DEMAND
- structured representative survey (e.g., per job title, O*NET)
- microscopic skill perturbations (e.g., patent data)
- unstructured real-time skills data (e.g., per worker or employer, online job postings and resumes)

REGIONAL / URBAN LABOR DEPENDENCIES
- employment distribution
- location-specific career data
- longitudinal employment trends

DATA ASSIMILATION

OUTPUT

A
Input

B

C
INTER-CITY MODELING

D
Output

FORECAST EMPLOYMENT TRENDS

POLICY INSIGHT

WORKER-CAREER INSIGHT

INTRA-CITY MODELING

Worker-Career Insight

Policy Insight

Forecast Employment Trends

School of Computing and Information

MIT Connection Science

HAI Stanford University Digital Economy Lab
Structural economic resilience

Network constraints on cities, careers, and economic resilience

Morgan R. Frank

School of Computing and Information
Future Work: Network embeddedness and unemployment risk

Occupational embeddedness:

\[ w^c_j = \sum_{i \in J} w^c_{ij} \]
How do Workers find Jobs?

2014 Nobel Prize in Economics for introducing Job Matching

\[
\begin{align*}
\dot{E} &= -\lambda U + M(U, V) \\
\dot{U} &= \lambda E - M(U, V)
\end{align*}
\]

where \( M(U, V) \propto U^\gamma V^{1-\gamma} \)

for \( \gamma \in [0,1] \)

this formulation is “a reflection at the aggregate level of the complex and varied pattern of hiring” because it misses the heterogeneous nature of skill matching
Urban Ecologies of Labor

\[ \dot{E}_j = -\lambda E_j + \alpha \sum_{i \in \text{Jobs}} w_{i,j} E_j^\gamma U_i^{1-\gamma} \]

\[ \dot{U}_j = \lambda E_j - \alpha \sum_{i \in \text{Jobs}} w_{i,j} E_i^\gamma U_j^{1-\gamma} \]

looks like Lotka-Volterra!
Urban Ecologies of Labor

\[ \dot{E}_j = -\lambda E_j + \alpha \sum_{i \in \text{Jobs}} w_{i,j} E_j^\gamma U_i^{1-\gamma} \]

\[ \dot{U}_j = \lambda E_j - \alpha \sum_{i \in \text{Jobs}} w_{i,j} E_i^\gamma U_j^{1-\gamma} \]

Reduces to...

\[ W^c = \sum_{i,j \in J^2} w^c_{ij} \]

\[ E_{\text{eff}}^c = \left( \sum_{j \in \text{Jobs}} E_j^c w_j^c \right) / W^c \]

\[ U_{\text{eff}}^c = \left( \sum_{j \in \text{Jobs}} U_j^c w_j^c \right) / W^c \]

\[ w_{\text{eff}}^c = \left( \sum_{j \in \text{Jobs}} (w_j^c)^2 \right) / W^c \]

Future Work: Network embeddedness and unemployment risk

\[ w^c_j = \sum_{i \in \text{Jobs}} w^c_{ij} \]

\[ W^c = \sum_{i,j \in \text{Jobs}} w^c_{ij} \]

\[ w^c_{\text{eff}} = \left( \sum_{j \in \text{Jobs}} (w^c_j)^2 \right) / W^c \]

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<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>log10 Total Employment (( T^c ))</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Job Connectivity (( w^c_{\text{eff}} ))</td>
<td>-1.75***</td>
<td>-1.32**</td>
<td>-0.005</td>
<td>0.64***</td>
<td>0.458</td>
<td>0.451</td>
</tr>
<tr>
<td>2000 Unemployment Rate (( R^c_{2000} ))</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Occupation Diversity (( N^c ))</td>
<td>0.70***</td>
<td>0.70***</td>
<td>0.68***</td>
<td>0.69***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment Diversity (( H^c ))</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( T^c \times R^c_{2000} )</td>
<td>-0.48</td>
<td>-0.35*</td>
<td>-0.072</td>
<td>-0.40*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( w^c_{\text{eff}} \times T^c )</td>
<td>0.093*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( w^c_{\text{eff}} \times N^c )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( w^c_{\text{eff}} \times H^c )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.031</td>
<td>0.119</td>
<td>0.535</td>
<td>0.552</td>
<td>0.541</td>
<td>0.565</td>
</tr>
<tr>
<td>adj. R²</td>
<td>0.026</td>
<td>0.105</td>
<td>0.528</td>
<td>0.539</td>
<td>0.530</td>
<td>0.542</td>
</tr>
</tbody>
</table>

\( p_{val} < 0.1^*, p_{val} < 0.01^{**}, p_{val} < 0.001^{***} \)
Future Work: Network embeddedness and unemployment risk

High Job Network Embeddedness

Financial Managers

Low Job Network Embeddedness

Skill Similarity \( (w_{ij}) \)

Financial Managers in 2015

Future Work: Network embeddedness and unemployment risk

| Dependent Variable: Avg. Annual Wage of Occupation $i$ in city $c$ in year |
|------------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Variable         | Model 1          | Model 2          | Model 3          | Model 4          | Model 5          |
| Employment Share in Occ. $i$ in year $c$ in year | $-0.012^{***}$ | $0.009^{***}$ | $0.001$ | $0.009^{***}$ | $0.001$ |
| % of Occ. $i$ emp. with Bachelor’s in year $c$ in year | $-0.056^{***}$ | $-0.014^{***}$ | $-0.015^{***}$ | $-0.014^{***}$ | $-0.015^{***}$ |
| Embeddedness of Occ. $i$ in year $c$ in year | $0.264^{***}$ | $0.266^{***}$ | $0.258^{***}$ | $0.266^{***}$ | $0.258^{***}$ |
| (Emp. Share)$\times$(Bachelors) | | | | | |
| (Emp. Share)$\times$(Embeddedness) | | | | | |
| (Bachelors)$\times$(Embeddedness) | | | | | |
| City Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.252 | 0.252 | 0.267 | 0.267 | 0.267 |
| adj. $R^2$ | 0.251 | 0.252 | 0.267 | 0.267 | 0.267 |

$p_{val} < 0.1^*$, $p_{val} < 0.01^{**}$, $p_{val} < 0.001^{***}$

Variables centered and standardized.

Dependent Variable: Avg. Annual Wage of Occupation $i$ in city $c$ in year

Future Work: Network embeddedness and unemployment risk

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\log_{10}$ Total Employment (2019)</td>
<td>0.958***</td>
<td>1.329***</td>
<td>1.294***</td>
<td></td>
</tr>
<tr>
<td>Job Connectivity ($w_{eff}$) (2019)</td>
<td>0.936***</td>
<td>$-0.376$***</td>
<td>$-0.358$***</td>
<td></td>
</tr>
<tr>
<td>interaction</td>
<td></td>
<td></td>
<td></td>
<td>0.018*</td>
</tr>
</tbody>
</table>

$R^2$ | 0.917 | 0.876 | 0.921 | 0.922 |

adj. $R^2$ | 0.917 | 0.875 | 0.921 | 0.922 |

$p_{val} < 0.1^*$, $p_{val} < 0.01^{**}$, $p_{val} < 0.001^{***}$

All variables centered and standardized.
Future Work: Network embeddedness and unemployment risk

Using the month of UI data in which each city experienced peak UI

Financial Managers

<table>
<thead>
<tr>
<th>High Embeddedness</th>
<th>Low Embeddedness</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="High Embeddedness" /></td>
<td><img src="image2" alt="Low Embeddedness" /></td>
</tr>
</tbody>
</table>

Using the month of UI data in which each city experienced peak UI

\[
P_{\text{state}}(ui|soc) = \frac{P_{\text{state}}(2soc|ui) \cdot P_{\text{state}}(ui)}{P_{\text{state}}(soc)}
\]

N=93,000

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
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<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\log_{10} \text{Avg. Wage})</td>
<td>0.032*</td>
<td>-0.041***</td>
<td>-0.010***</td>
<td></td>
</tr>
<tr>
<td>(\log_{10} \text{Total Employment})</td>
<td>-0.577***</td>
<td>-0.637***</td>
<td>-0.638***</td>
<td></td>
</tr>
<tr>
<td>Occ. Embeddedness</td>
<td>-0.279***</td>
<td>-0.027**</td>
<td>-0.265***</td>
<td>-0.024**</td>
</tr>
<tr>
<td>City F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>2-Digit SOC F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>R^2</td>
<td>0.675</td>
<td>0.889</td>
<td>0.677</td>
<td>0.889</td>
</tr>
<tr>
<td>adj. R^2</td>
<td>0.674</td>
<td>0.889</td>
<td>0.675</td>
<td>0.889</td>
</tr>
</tbody>
</table>

\(p_{val} < 0.1^*, p_{val} < 0.01**, p_{val} < 0.001***\)

Using the month of UI data in which each city experienced peak UI

\[
P_{\text{city}}(ui|soc) = \frac{P_{\text{state}}(2soc|ui) \cdot P_{\text{city}}(ui)}{P_{\text{city}}(soc)}
\]

Dependent Variable: \(\log_{10} P_{\text{state}}(ui|soc)\)

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<th>Model 4</th>
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<tbody>
<tr>
<td>(\log_{10} \text{Avg. Wage})</td>
<td>0.032*</td>
<td>-0.032***</td>
<td>0.001*</td>
<td></td>
</tr>
<tr>
<td>(\log_{10} \text{Total Employment})</td>
<td>-0.637***</td>
<td>-0.637***</td>
<td>-0.638***</td>
<td></td>
</tr>
<tr>
<td>Occ. Embeddedness</td>
<td>-0.288***</td>
<td>-0.009*</td>
<td>-0.276***</td>
<td>-0.009*</td>
</tr>
<tr>
<td>City F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>2-Digit SOC F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>R^2</td>
<td>0.697</td>
<td>0.958</td>
<td>0.698</td>
<td>0.958</td>
</tr>
<tr>
<td>adj. R^2</td>
<td>0.696</td>
<td>0.958</td>
<td>0.697</td>
<td>0.958</td>
</tr>
</tbody>
</table>

\(p_{val} < 0.1^*, p_{val} < 0.01**, p_{val} < 0.001***\)
Summary

• Use empirical skill profiles for US occupations to relate occupations and predict job transitions.

• Modeling US cities as occupation networks, we find that workers tend to decrease their employment-weighted embeddedness over their career.

• City pairs with large average combined embeddedness exhibit greater flows of spatial mobility.

• Using a similar idea to occupation embeddedness, cities with high job connectivity were more resilient during the Great Recession.
Related Reading

- Small cities face greater impact from automation
  M.R. Frank, L. Sun, M. Cebrian, H. Youn, I. Rahwan
  Journal of the Royal Society Interface, 2018

- Unpacking the polarization of workplace skills
  A. Alabdulkareem*, M.R. Frank*, L. Sun, B. AlShebli, C. Hidalgo, I. Rahwan
  *joint first author
  Science Advances, 2018

- Universal resilience patterns in labor markets
  E. Moro*, M.R. Frank*, A. Pentlan, A. Rutherford, M. Cebrian, I. Rahwan
  Nature Communications, 2021

- Network constraints on worker mobility: how workplace skills determine a worker’s next move
  M.R. Frank, E. Moro, A. Rutherford, I. Rahwan
  (under review at Nature Communications)

- Towards Understanding the Impact of AI on Labor
  M.R. Frank, D. Autor, J.E. Bessen, E. Brynjolfsson, M. Cebrian, D.J. Deming,
  M. Feldman, M. Groh, J. Lobo, E. Moro, D. Wang, H. Youn, I. Rahwan
  Proceedings of the National Academy of Science, 2019
Network constraints on cities, careers, and economic resilience

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The Team
Lots of data

- **Occupational skill profiles:** US Bureau of Labor Statistics (BLS) O*NET database from 2010-2018

- **Urban Employment by Occupation:** BLS Occupation employment statistics from 2010-2018

- **Workers’ Career Trajectories:**
    - nationally-representative, but only sparsely samples the space of occupation pairs
  - millions of worker resumes from two sources: Burning Glass Technologies and FutureFit AI
    - good coverage for a biased sample of industries

- **Spatial Mobility between US cities:**
  - US Census migration from 2013-2018
  - US Bureau of Transportation Statistics enplaned passenger data spanning 2013-2018
Skill similarity improves models of individual career mobility

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{skillsim}(j, j')$</td>
<td>0.026***</td>
<td>0.036***</td>
<td>0.036***</td>
<td>0.036***</td>
</tr>
<tr>
<td>Log-10 Total Employment ($T(j, j')$)</td>
<td>0.479***</td>
<td>0.484***</td>
<td>0.511***</td>
<td>0.517***</td>
</tr>
<tr>
<td>Cognitive/Physical Similarity ($CP(j, j')$)</td>
<td>0.135***</td>
<td>−0.125***</td>
<td>−0.125***</td>
<td>−0.125***</td>
</tr>
<tr>
<td>$\text{skillsim}(j, j') \times CP(j, j')$</td>
<td>0.019***</td>
<td>0.019***</td>
<td>0.019***</td>
<td>0.019***</td>
</tr>
<tr>
<td>$\text{skillsim}(j, j') \times T(j, j')$</td>
<td>0.062***</td>
<td>0.062***</td>
<td>0.062***</td>
<td>0.062***</td>
</tr>
<tr>
<td>$CP(j, j') \times T(j, j')$</td>
<td>0.008*</td>
<td>0.008*</td>
<td>0.008*</td>
<td>0.008*</td>
</tr>
</tbody>
</table>

Dependent Variable: $\log_{10}$ Job Transitions

Year F.E. Yes Yes Yes Yes

$R^2$ 0.238 0.255 0.300 0.312

adj. $R^2$ 0.238 0.255 0.300 0.312

Job transition rates from the Burning Glass Technologies resume data (1.2 million career moves). Variables are centered and standardized.

Job transition rates from the FutureFit.Ai resume data (3.2 million career moves). Variables are centered and standardized.